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Measuring Mortgage Refinancing in Chile

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Measuring Mortgage Refinancing in Chile*

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Abstract. Refinancing is a central feature of mortgage markets and an important determinant of household wealth accumulation, monetary policy transmission, and mortgage pricing. Yet refinancing is not always directly observed in regulatory data. We propose practical methods to detect refinancing events using individual-level data on mortgage balances and originations, which is often available from regulators and credit bureaus, even when refinancing itself is not explicitly recorded. We apply these methods to administrative data from the Chilean mortgage market to characterize the extent and evolution of refinancing in that setting. Our findings suggest that mortgage refinancing in Chile is quantitatively limited and that most of it is driven by interest rate reductions through rate-and-term refinancing.

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1 Introduction

Mortgage refinancing, whereby a borrower replaces their current mortgage with a new loan—typically to secure more favorable contract terms through a lower interest rate or reduced monthly payments—plays an important role for households and the broader economy. Recent economic research emphasizes the impacts of mortgage refinancing. For instance, refinancing can significantly impact household wealth accumulation, with important implications for inequality (Beraja *et al.*, 2018). Moreover, refinancing is a key channel for the transmission of monetary policy, as borrowers can capitalize on lower market interest rates (Eichenbaum *et al.*, 2022; Berger *et al.*, 2024).

Most financial regulators worldwide require lenders to record loan contract terms at origination, as part of their oversight efforts. In some countries, lenders must report whether a mortgage origination constitutes a refinancing of a borrower's previously held mortgage. For example, in the US, lenders must report loan-level information under the Home Mortgage Disclosure Act (HMDA), including refinancing events. Regulators in Canada and the UK impose similar reporting requirements on lenders. In Chile, by contrast, the Financial Markets Commission (CMF) does not require lenders to report whether a mortgage constitutes a refinancing, despite having highly detailed reporting requirements. As a consequence, policymakers and researchers are unable to directly quantify the extent of refinancing in the Chilean mortgage market.

In this paper, we describe several strategies for recovering refinancing events from administrative borrower-level data on mortgage origination and repayment. These methods have been developed in the context of research on the drivers of refinancing in the Chilean market (Bhattacharya *et al.*, 2026) and complement the efforts of the Chilean Central Bank to measure refinancing events using similar data (Banco Central de Chile, 2019). In practice, we attempt to disentangle mortgage refinancing from other changes in mortgage borrowing through their effects on an individual's mortgage borrowing stocks and origination flows over time. These indicators will exhibit distinct patterns depending on whether a mortgage refinancing occurs within the borrower's home bank or across banks, whether it is a rate-and-term or cash-out/cash-in refinancing, and whether it is recorded as an origination; we develop different identification algorithms accordingly. While we implement these strategies in the Chilean context, these can be applied to other settings where similar data are available, yet refinancing is not directly flagged (e.g., Denmark, Italy, and Mexico, among others).

Our findings suggest that mortgage refinancing plays a relatively limited role in the Chilean mortgage market. On average, the probability that a mortgage borrower refinances in a given month is 0.1 percent, and refinancing accounts for about 11 percent of all mortgage originations. These numbers are well below comparable estimates for the United States, where refinancing plays an important role in the mortgage market (see, e.g., Fuster *et al.* 2019; Freddie Mac 2020). Among the refinancing events we detect, the vast majority are rate-and-term operations, most of which result

in a reduction of the borrower's interest rate. This also contrasts with the United States, where cash-out refinancing is much more common (Bhutta and Keys, 2016). Finally, most refinancing in Chile occurs within the incumbent bank: only about one-fourth of the detected refinancing events involve switching lenders. Taken together, these patterns suggest that refinancing in Chile is used primarily to reprice existing mortgage debt but remains a relatively uncommon margin of adjustment compared with other settings. However, these figures should be interpreted with some caution, as our detection algorithms are likely to miss some refinancing events, particularly those involving cross-bank cash-out or cash-in operations.

This paper contributes to the empirical literature on the measurement of mortgage refinancing. A key feature of previous work is that, as in our case, the administrative data do not directly identify refinancing events; however, by linking successive mortgage contracts for the same borrower, the authors can identify them. For example, Di Maggio *et al.* (2020) exploit this linked-loan structure to measure refinancing and study the refinancing channel of monetary policy; Beraja *et al.* (2018) do so to study regional heterogeneity in refinancing; and Agarwal *et al.* (2017) do so to study the impact of the HARP program in the aftermath of the Great Recession. Our approach is similar to that in these studies, in which the key principle is that refinancing replaces previously held loans; by linking the data at the borrower level, we can measure both the timing of refinancing and its impact on mortgage balances and contract terms. These methods may be helpful for both researchers and regulators interested in quantifying mortgage refinancing.

The rest of this paper is structured as follows: Section 2 describes the data we utilize; Section 3 defines the types of refinancing we capture and describes the algorithms we use to do so; Section 4 presents stylized facts regarding mortgage refinancing in Chile; and Section 5 concludes with a brief discussion.

2 Data

We work with two sources of granular data collected by CMF. First, we observe the outstanding balance a borrower holds with each lender at the end of each month. We call these the borrowing *stocks*. These data are common in most credit registries, and often provide information on balances but not on contract terms. Second, we observe all mortgage originations, including the date, lender, and contract terms such as amount, interest rate, and maturity. We call these the origination *flows*. In our setting, originations do not flag refinancing events; this motivates the measurement methods we describe in this paper. We are able to link mortgage stocks and flows at the borrower-lender-month level, and hence track how borrowing stocks vary around originations.[1]

We work with a representative sample of borrowers who had outstanding mortgage contracts in the Chilean mortgage market in 2021. We observe these borrowers' activity in the market during

[1] A challenge for the identification of refinancing events is that the data on mortgage stocks is aggregated to the borrower-bank level, instead of identifying individual mortgages held by a borrower from a given lender.

Table 1: Summary statistics

	Mean	SD	p10	p50	p90
A. Borrower over the sample					
Number of distinct lenders	1.34	0.67	1.00	1.00	2.00
Number of originations	1.09	1.34	0.00	1.00	2.00
Years active	9.07	3.17	3.92	10.17	12.00
Annual income (UF)	619.78	573.35	139.87	461.28	1248.34
Age	45.51	10.64	32	44	60
B. Origination terms					
Loan amount (UF)	2726.04	2345.85	949.00	2039.03	5264.00
Interest Rate (p.p.)	3.58	0.94	2.30	3.65	4.70
Maturity (years)	22.36	6.00	15.14	20.75	30.46
Monthly Payment (UF)	15.96	28.23	5.73	11.32	28.91

Notes: Panel A provides summary statistics at the borrower level ($N = 49,859$). Panel B provides summary statistics at the mortgage origination level, excluding loan reprogrammings ($N = 40,794$). Income and age data come from CMF records.

the period of January 2012–December 2023. The sample includes 49,859 individual borrowers over the sample period who borrow from 17 financial institutions, capturing most of the relevant lenders in the country. The average borrower holds mortgages from 1.34 lenders at some point during the sample period and displays 1.09 mortgage originations in our sample—in addition to mortgages held since before our sample period. The distribution of these variables is skewed, with the median borrower interacting with only one lender and having one origination during the sample, whereas the 90*th* percentile reaches two for each.[2]

The average contract in the originations data—including both new mortgages and refinancing—has a borrowed amount of 2,726 UF, a 22-year maturity, and a 3.6 percent annual interest rate. Combined, these terms imply that the average origination requires a monthly payment of 16 UF, equivalent to roughly a third of the average borrower income.[3]

[2]About 24 percent of originations are classified as *reprogrammings* of existing mortgages, which often restructure loan repayment schedules without changing underlying loan terms. These were used extensively as relief in 2020 during the COVID-19 pandemic. We exclude these originations when computing these descriptive statistics.

[3]Throughout, we measure amounts in UF (*Unidades de Fomento*), an inflation-adjusted monetary unit commonly used in the Chilean market. For reference, a UF was equal to 45.67 US dollars by March 2026.

3 Measuring Refinancing

3.1 Types of Refinancing

We focus on the three main categories of refinancing events that we can potentially identify, given the available data:[4]

1. *Rate-and-term refinancing*: A borrower fully prepays an existing mortgage to obtain a new one, typically with more favorable terms, such as a lower interest rate or a different loan term and roughly the same principal.

2. *Cash-out refinancing*: A borrower takes out a new loan using their home as collateral, receives cash at closing, and pays off their existing mortgage.

3. *Cash-in refinancing*: A borrower replaces their current mortgage with a new loan for a smaller principal by contributing extra funds at closing.

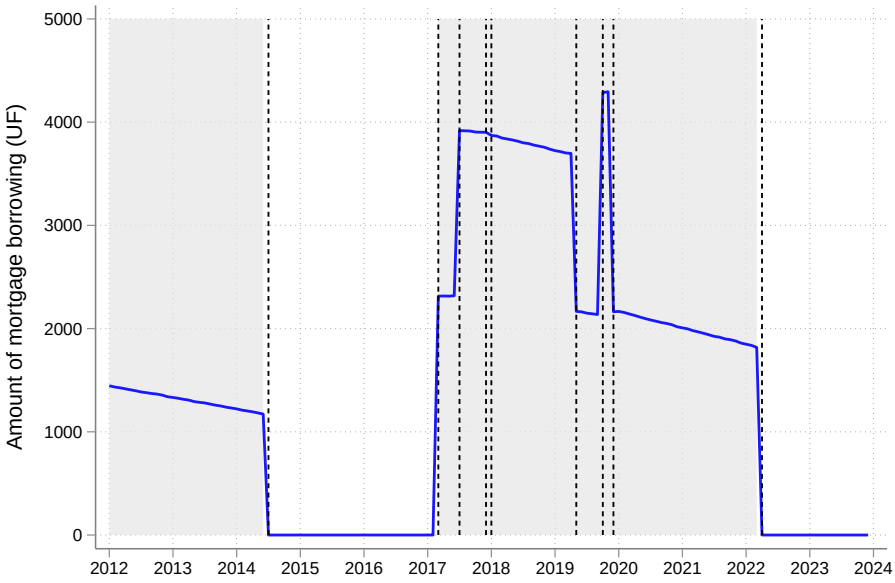
A researcher's ability to detect refinancing events of this nature in the data comes from their distinct impacts on the evolution of borrower-level origination flows and mortgage borrowing stocks. These form the basis of our strategies for detecting refinancing events. For instance, whenever new mortgages are recorded as originations, a new origination of an amount similar to the previously held mortgage, keeping the overall borrowing stock unchanged, is consistent with rate-and-term refinancing. Similarly, a new origination of a different amount than the previously held mortgage, which replaces the latter, is consistent with cash-out or cash-in refinancing. However, a refinancing event may not always be recorded as a new origination. In such cases, a change in the slope of a borrower's mortgage borrowing stock over time, without a discrete change in the level, is consistent with rate-and-term refinancing. Finally, when a new origination at one bank occurs around the same time as a comparable drop in the borrower's mortgage balance at another bank, this suggests that the borrower switched lenders on an existing loan. We develop four algorithms for detecting refinancing based on these principles.

3.2 Key Data Concepts

Before presenting our algorithms for detecting refinancing events, we introduce two data concepts that will help describe them. For illustration, Figure 1 displays an example of the evolution of the mortgage balance of a borrower at a particular lender during the sample period, which displays several jumps in the borrowing stock as well as changes in the slope of this stock over time.

[4]This classification follows standard taxonomies used in countries that record refinancing. For example, the Federal Housing Administration, Fannie Mae, and Freddie Mac in the US include these as the three main refinancing types, along with *streamlined refinancing*.

Figure 1: Example of mortgage borrowing stock over time



Notes: Mortgage borrowing stock held by an individual borrower over time (blue). Gray shaded areas are individual borrowing *spells*, vertical dashed black lines are balance *jumps* marking the different *segments* within a spell.

Borrowing Spell. In the borrowing stock data, we observe the monthly mortgage borrowing balances held by a borrower with each lender. We define a borrowing spell as a sequence of months during which a borrower has a positive balance with a given lender. Note that since we cannot identify individual loans directly in the stock data, we cannot define spells at the borrower-lender-loan level but only at the borrower-lender level. Figure 1 shows a borrowing spell that starts in 2017 and finishes in 2022. The events marking the beginning and end of this spell may be some combination of new originations, refinancing, and full prepayment, which we attempt to disentangle below.

Balance Jumps and Segments. Borrowing amounts are not always smoothly decreasing within a borrowing spell as the borrower repays the mortgage. Rather, the data often show discrete increases or decreases in a borrower's mortgage balance with a lender. We define those discrete changes as *balance jumps*. These jumps may be driven by new originations, refinancings, partial prepayments, or full prepayments. Spells naturally begin with a jump and, in some cases, also end with a jump. Between two balance jumps, balances often evolve smoothly. We define those intervals as *segments*. Figure 1 shows an example borrower, where the dashed black vertical lines indicate how a sequence of jumps splits a borrowing spell into segments.

3.3 Algorithms for Refinancing Detection

We develop four algorithms that operationalize distinct approaches for identifying refinancing events. Table 2 summarizes the goals and data requirements of each algorithm. Algorithms 1 and 2 used balanced panels for each observed borrower-lender combination, filling in empty periods with zero balances. Algorithm 3 uses unbalanced borrower-lender panels tracking individual borrowing spells. Algorithm 4 focuses on *jumps* and *segments* and matches them by borrower, date, and quantity. Throughout, we use the notation ℓ for borrowing stocks and o for origination flows. Moreover, we use the subscripts i, b, and t to denote the borrower, bank, and time, respectively. We provide further details about how we prepare the data on borrowing stocks and originations in Appendix A.1.

3.3.1 Algorithm 1: Rate-and-term Refinancing using Originations and Borrowing Stocks

This algorithm assumes that when an observed origination flow is a rate-and-term refinancing event, the mortgage being refinanced is paid off and replaced. As a result, borrowing stock under the new contract approximately matches the borrowing stock right before the origination. Instead, if the origination is an additional loan, the principal from that origination is added to the pre-existing balance. To identify rate-and-term refinancing events, we thus simulate the borrower's mortgage stock around the origination event as if it was not a refinancing, and hence simply add that new loan to the pre-existing balance. We then compare that simulated borrowing stock to the observed one; if the difference between them is close to the amount of the originated mortgage, then that origination was a rate-and-term refinancing.

To implement this strategy, we use a panel dataset that captures all borrower-lender spells in our data and split each one into segments. Around each origination, we construct a counterfactual borrowing stock path under the assumption that the new loan adds to rather than replaces the pre-existing balance. Let $t = 0$ denote the month of the origination, and let Δ_{ib} denote the average monthly change in the borrowing stock in the preceding segment. The counterfactual borrowing stock $\tilde{\ell}_{ibt}$ evolves as:

$$\tilde{\ell}_{ibt} = \tilde{\ell}_{ib,t-1} + o_{ibt} + \Delta_{ib}, \quad t = 0, 1, \ldots, T$$

where o_{ibt} is the origination principal at t, set to zero in months without an origination, and where $\tilde{\ell}_{ib,-1} \equiv \ell_{ib,-1}$, since we take the stock balance in the month before the origination at $t = 0$ as the starting point for our simulation.

Then, for the periods $t = 1, ..., T$, we compute the statistic:

$$\kappa_{ibt} = \frac{\tilde{\ell}_{ibt} - \ell_{ibt}}{\sum_{k=0}^{t-1} o_{ibk}} \tag{1}$$

which indicates that an origination essentially replaces the previously held loan whenever κ_{ibt} is

Table 2: Summary of algorithms used for refinancing detection

		Data requirements	
Algorithm	Type of refinancing	Stocks	Flows
1	Rate-and-term (within bank)	✓	✓
2	Cash-out / cash-in (within bank)	✓	✓
3	Rate-and-term (within bank)	✓	✗
4	Rate-and-term (across banks)	✓	✓

close to one, hence that the origination is part of a rate-and-term refinancing event. In particular, we flag an origination as a refinancing event whenever $\kappa_{ibt} \geq \bar{\kappa}$ for H out of T months following the origination, with $\bar{\kappa}$ being a tolerance parameter that we choose.[5] Figure 2-a provides an example of a refinancing event detected through this strategy. We implement this test for all mortgage originations in the data. We provide further details and additional checks for false positives in Appendix A.2.

3.3.2 Algorithm 2: Cash-out/cash-in Refinancing using Originations and Borrowing Stocks

Cash-outs are refinancing events where the new loan's principal is noticeably higher than the borrower's outstanding balance at the time of refinancing. Under this definition, an origination observed in month t for a borrower with a positive pre-existing borrowing stock from a bank is identified as a cash-out refinancing if it meets the following criteria:

1. The origination amount exceeds the borrower's mortgage balance in the prior period:

$$(1 + \gamma)\, \ell_{ib,t-1} < o_{ibt} \tag{2}$$

2. The borrower's mortgage balance following the origination is close to the origination amount:

$$\left| \frac{\ell_{ib,t+s}}{o_{ibt}} - 1 \right| < \phi \tag{3}$$

3. The net change in borrowing stock is small relative to the origination amount. If the origination was instead an additional loan, the borrowing stock change would be close to the origination amount, and the ratio below would be near one:

$$\left| \frac{o_{ibt}}{\ell_{ib,t+s} - \ell_{ib,t-1}} \right| > 1 + \psi \tag{4}$$

[5]The sum in the denominator of equation (1) accommodates cases with multiple sequential originations. In such cases, a refinancing late in the sequence can cause preceding originations to also be flagged as refinancing. We guard against such double-counting when implementing the algorithms, as discussed in Appendix A.1.

where ϕ, ψ, and γ are positive tolerance parameters for the respective conditions. Figure 2-b provides an example of a cash-out refinancing detected using this strategy. Criterion (2) compares quantities dated at or before origination and is evaluated once. Criteria (3) and (4) instead compare the origination to the borrowing stock that follows it, and the stock data occasionally record the new loan before removing the one it replaced, causing the aggregate balance to overshoot before correcting itself. As in Algorithm 1, we therefore evaluate them at each horizon $s = 1, \ldots, T$ after the origination, and flag a cash-out when both hold in at least H of those T months.

Cash-in refinancings are conceptually similar to cash-outs and mirror their behavior: the existing loan is fully prepaid, and a new one is originated, in this case with a lower balance—rather than a higher one, as in a cash-out—because the borrower brings cash for closing instead of receiving cash. Therefore, the criteria for cash-in events are the same, with the inequality in equation (2) reversed, such that the origination amount must be smaller than the borrower's outstanding balance before the origination, beyond possible closing costs: $(1 - \gamma)\, \ell_{ib,t-1} > o_{ibt}$. We discuss our choices for γ, ϕ, and ψ, and additional details in Appendix A.3.

3.3.3 Algorithm 3: Rate-and-term Refinancing using Borrowing Stocks Only

In the absence of origination data, the scope for detecting refinancing events is limited to what we can infer from changes in a borrower's mortgage borrowing stock over time. Using that data, it is not feasible to determine whether jumps in borrowing stocks stem from cash-out or cash-in refinancing or from new mortgages added to the outstanding stock. Hence, we restrict our attention to detecting rate-and-term refinancing within a bank, which should appear in borrowing stock data as a change in the borrowing stock's slope over time, without a noticeable jump in the stock itself.

For this purpose, we employ a structural break test (Bai and Perron, 1998). Let $\Delta\ell_{ibt}$ be the monthly change in the borrowing stock of borrower i at bank b. For simplicity, we abstract from its non-linear evolution over the loan's maturity and model it as a piecewise-constant stochastic process:

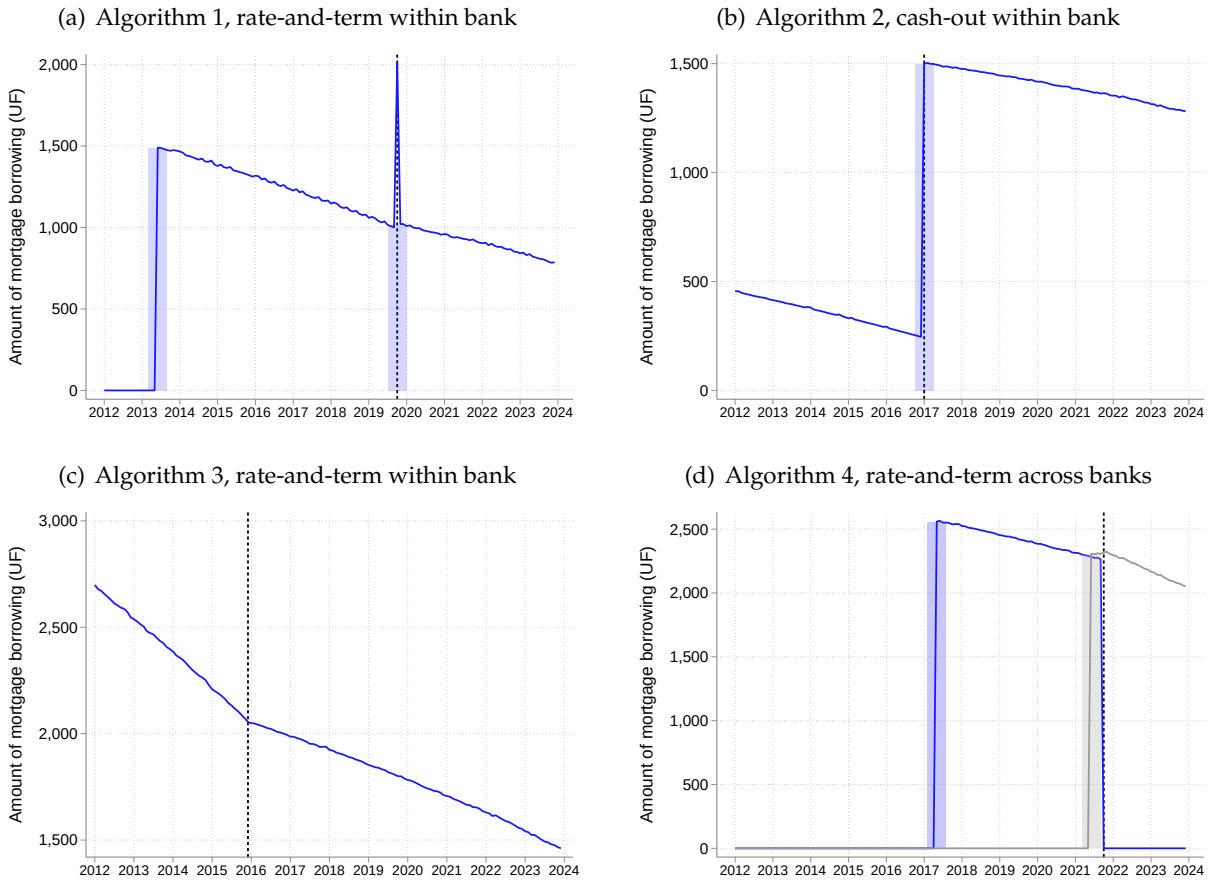
$$\Delta\ell_{ibt} = \alpha_{ibt} + \varepsilon_{ibt}$$

where ε_{ibt} is a mean-zero error term. The structural break test compares the null of a constant value for α over time against the alternative of a piecewise-constant α_{ibt} that shifts at a specific moment, τ. A structural break in the $\Delta\ell_{ibt}$ series points to a discrete change in a borrower's monthly payments to a lender, which, in the absence of a contemporaneous structural break in the borrowing stock, indicates a rate-and-term refinancing event.

In practice, we proceed as follows. We first compute a Wald test to detect structural breaks in $\Delta\ell_{ibt}$ for each individual borrowing spell.[6] For borrowing spells with an F-statistic above a

[6]For implementation, we adopt the methodology in Ditzen *et al.* (2025), which first identifies the period τ^d_{ibt} in the

Figure 2: Examples of detected refinancing events



Notes: Examples of refinancing events detected by each algorithm, as indicated by the respective captions. Each panel displays an individual borrower. Lines indicate the mortgage borrowing stock over time at a lender (blue, gray); vertical bars indicate the magnitude of new mortgage originations (blue, gray); and vertical dashed lines indicate the date of the refinancing event. Panel (d) shows a borrower's mortgage borrowing at two separate lenders.

given threshold f^d, we run an equivalent test on the borrowing stock, ℓ_{ibt}, likewise heuristically modeling the stock as following a piecewise-constant stochastic process $\ell_{ibt} = \beta_{ibt} + \epsilon_{ibt}$. For this second test, the candidate break date τ^s_{ibt} is the closest balance jump within T periods of the slope break; if no such jump exists, we use the same as before, $\tau^s_{ibt} = \tau^d_{ibt}$. A break in the borrowing stock is considered significant if the F-statistic from the second test exceeds a stricter threshold f^s and the break magnitude itself clears both an absolute and a relative threshold relative to the mortgage balance before the break. Figure 2-c provides an example of a refinancing event detected with this strategy. We provide details on parameter choices, a procedure to smooth borrowing stock slopes, and additional checks for false positives in Appendix A.4.

series that would maximize the F-statistic of the Wald test, and then runs the test for that particular τ^d_{ibt}.

3.3.4 Algorithm 4: Rate-and-term Refinancing across Banks

Whereas the previous strategies focus on refinancing within a lender, this algorithm captures rate-and-term refinancing across banks. The strategy essentially consists of matching sharp contemporaneous shifts in a given borrower's mortgage borrowing stock across banks, such that the outflow from one bank roughly compensates for the inflow at another bank associated with a new loan origination.

We implement this strategy as follows. We start by identifying all borrowing stock jumps for a given borrower i at each lender in the market. For each jump, we search for all other borrowing stock jumps for the same borrower at other banks that occur within a short time window afterward. We look for combinations (tuples) in which each stock jump is associated with a different lender, and the amounts approximately cancel out. To illustrate: suppose borrower i experiences a large decline in their mortgage balance at lender A at time t, followed by a corresponding increase at lender B at time $t + \lambda$, with λ capturing a short window after the event. We identify this as a refinancing event if:

$$\left| \frac{\Delta \ell_{iA,t} + \Delta \ell_{iB,t+\lambda}}{\Delta \ell_{iB,t+\lambda}} \right| < \eta \tag{5}$$

which indicates that the inflow and outflow match closely, within tolerance η. The denominator simply scales the difference in the numerator. If met, this condition would suggest that borrower i refinanced the mortgage they held at lender A with lender B. Note that in practice, we do not assume that the outflow from A precedes the inflow into B.

Finally, in order to identify these as refinancing events, we look for a contemporaneous mortgage origination by the borrower that matches the inflow side of the tuple. While this may be unnecessary, in our setting, tuples without a matching origination almost exclusively correspond to mass title transfers triggered by bank mergers during our sample period rather than individual borrowers refinancing across banks. In addition, this requirement allows us to recover the terms of the new loan and, hence, the realized gains from refinancing.

When implementing this algorithm, we start with all pairwise combinations of lenders from which the borrower has obtained mortgages as illustrated in equation (5), and then check whether larger combinations of lenders meet this condition, including more terms in the left-hand side of (5) as needed. We proceed iteratively until exhausting all possible combinations of lenders. Figure 2-d illustrates a refinancing event detected with this strategy. We provide further details in Appendix A.5.

3.4 Basic Results and Limitations

Our strategies identify several thousand refinancing events in the sample. Table 3 reports the distribution of these events across the four algorithms. Our findings imply that an equivalent of 124 thousand refinancing events occurred nationwide between 2012 and 2023. In the next section,

Table 3: Refinancing detections by algorithm

Algorithm	Type of refinancing	Number	Share
1	Rate-and-term (within bank)	65,660	52.88%
2	Cash-out / cash-in (within bank)	10,480	8.44%
3	Rate-and-term (within bank)	14,760	11.89%
4	Rate-and-term (across banks)	33,260	26.79%

Notes: Number and types of refinancing events detected by each algorithm. For counts, we use sample weights to report representative results for the full market in 2021.

we provide some descriptive analysis to contextualize these findings.

While fairly comprehensive, our proposed approach has limitations. In particular, none of our algorithms can capture cash-out or cash-in refinancing in two cases: either without a corresponding origination in the data or across lenders. We stop short of attempting to identify refinancing in these cases, since achieving a similar level of confidence would be challenging. For instance, consider cash-out or cash-in refinancing without a contemporaneous origination. In the absence of a jump in a borrower's mortgage stock in the surrounding period, we can confidently flag a change in the slope of such stock at a bank as rate-and-term refinancing. In that case, however, it would be difficult to determine whether the jump in borrowing stock was driven by cash-out (cash-in) refinancing or by a new mortgage (a large lump payment). Similarly, for the case of refinancing across lenders, we could attempt to detect cash-in or cash-out refinancing by using a variant of algorithm 4 that allowed for inflows and outflows of different total amounts across banks. However, that would increase the risk of linking unrelated transactions and, hence, the likelihood of false positives. In summary, our strategies could be extended to capture these refinancing events, albeit with lower confidence.

These limitations suggest we may be underestimating the extent of refinancing in the Chilean market with these strategies. We attempt to assess the extent of underestimation by turning to our results in Table 3. The ratio of rate-and-term to cash-out/cash-in within-bank refinancing events we identify based on observed origination flows is roughly 6:1. Applying that ratio to the two cases discussed in the previous paragraph would imply that we would be missing 14 percent of refinancing events across lenders, and six percent of overall refinancing events.[7] Regardless, there are other reasons to argue that our results may underestimate the overall amount of mortgage refinancing, many of which relate to our attempts to minimize false positives. For example, the

[7]This is likely an upper bound, since (i) the share of cash-out or cash-in refinancing events without an origination counterpart is likely lower than it is for rate-and-term refinancing, and (ii) the barriers that make that type of refinancing rare in the Chilean setting would plausibly be higher when doing it across lenders. For instance, the Portability Law introduced in 2020 to facilitate switching lenders was, in the case of mortgages, largely intended for rate-and-term refinancing, thereby maintaining the loan's existing obligations while adjusting the contract rate. See `https://www.gob.cl/portabilidadfinanciera/` for details.

timing between originations and changes in borrowing stocks is not always exact, and we adopt conservative tolerance parameters for the algorithms. We provide more details in the Appendix, including a sensitivity analysis of how our parameter choices affect the total number of refinancing events we detect.

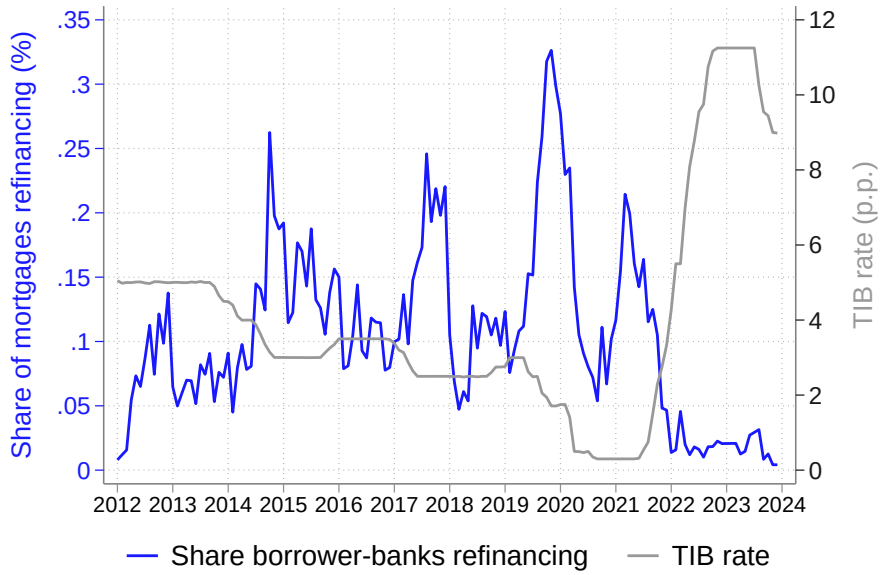
4 Descriptive Evidence on Mortgage Refinancing

Number and Types of Refinancing. Table 3 shows that most of refinancing corresponds to rate-and-term refinances, which account for the majority of detections. By contrast, the algorithms targeting cash-out and cash-in refinancing account for a much smaller share of detected events. Moreover, among the latter, 99 percent of the events that we detect correspond to cash-out refinancing. The dominance of rate-and-term refinancing is consistent with existing evidence for Chile (Banco Central de Chile, 2019), and contrasts with the United States, where refinancing more frequently involves equity extraction through cash-out refinancing (Bhutta and Keys, 2016), with the proportion of cash-out refinancing fluctuating between 15 and 90 percent over our sample period (Freddie Mac, 2023). Importantly, home rate-and-term refinancing events overwhelmingly lower borrowing costs: approximately 82 percent of these operations lead to interest rate reductions, whereas eight percent of them leave interest rates unchanged. Quantitatively, interest rates fall by an average of 0.87 percentage points following the home rate-and-term refinancing events we detect. These patterns are consistent with the idea that most refinancing activity is motivated by declines in market mortgage rates rather than by equity extraction or additional borrowing.

Relationship to Mortgage Portability Regulation. The Portability Law, introduced in 2020, provided an infrastructure to facilitate switching across banks. When switching banks, borrowers often attempt to negotiate mortgage terms, as in a standard refinancing process. As part of this regulation, banks must report to CMF all loans that switched between lenders. We use these data to benchmark the refinancing events detected by our algorithms.

First, we note that over the period for which the portability data are available, up to 88 percent of reported portability events are flagged by our procedures as refinancing events. This finding serves as validation and suggests our algorithms are indeed detecting refinancing events that effectively occurred. Second, refinancing does not always occur under the portability regulation framework; it can also occur through direct interactions between borrowers and banks that are not recorded. Whereas the portability data mechanically do not capture these refinancing events, our algorithms do detect a sizable amount of them. In practice, we find that for each portability refinancing event, there are 4.9 such events that are not recorded in the portability data for the same period, 3.8 of which have a matching origination in our flows data. Taken together, these results (i) provide confidence in our measurement of mortgage refinancing, and (ii) suggest that conclusions regarding refinancing based on portability data alone would likely lead to underestimates of

Figure 3: Propensity to refinance mortgages over time



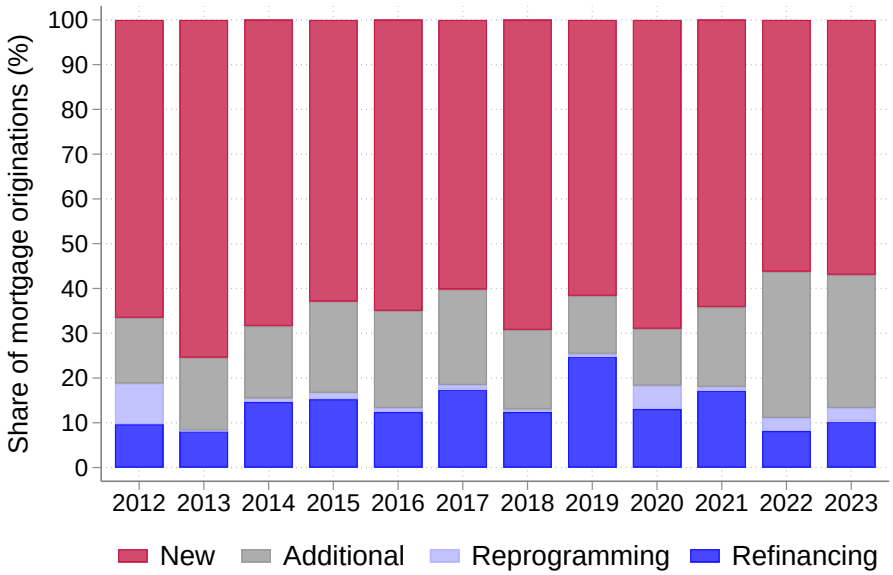
Notes: This figure shows the propensity that any borrower holding a mortgage in a given month refinances (blue, left axis), as well as the monthly TIB rate, which proxies for banks' funding costs (gray, right axis). Propensity is computed as total monthly refinancing events over total borrower-lender observations with positive balances.

refinancing activity in the Chilean market.

Propensity to Refinance Over Time. Figure 3 plots the monthly propensity to refinance in our data, measured as the share of outstanding mortgage debt that is refinanced in a given month. The average propensity to refinance an outstanding mortgage is 0.1 percent per month. For context, this propensity to refinance is low relative to that of the United States. For instance, Fuster *et al.* (2019) report an average monthly refinancing propensity of 0.54 percent between 2010 and 2016, whereas Beraja *et al.* (2018) document monthly refinancing propensities of between 0.4 and 1.2 percent in the period following the Great Recession. That said, there are relevant institutional differences between these markets that may drive this heterogeneity in refinancing activity.

Despite its low average level, refinancing activity in Chile exhibits meaningful time-series variation. Figure 3 suggests refinancing increases when funding costs decline, as in 2014 and again around 2019, and falls sharply when funding costs rise, as in 2022 and afterward. This pattern is consistent with the view that refinancing responds to the incentives created by movements in mortgage funding costs. Figure 3 also shows no clear increase following the introduction of portability regulation in the Chilean market in late 2020, which aimed to reduce the costs of switching banks (Comisión para el Mercado Financiero, 2020). That said, the reform's timing overlaps with both the pandemic and the pronounced rise in interest rates, so the figure is not well

Figure 4: Mortgage refinancing as a share of originations



Notes: This figure shows the breakdown of mortgage origination types in each year, including borrowers that obtain new mortgages (red), those that obtain additional mortgages at banks where they already held mortgages (gray), the reprogramming of previously held mortgages (light blue), and mortgage refinancing (blue). Originations are aggregated to the borrower-lender-month level as described in Appendix A.1. These shares are weighted by origination amount. We note that an unweighted version of this figure would show a similar pattern, except for 2020, when banks implemented a large number of small reprogrammings, which dominated other origination types.

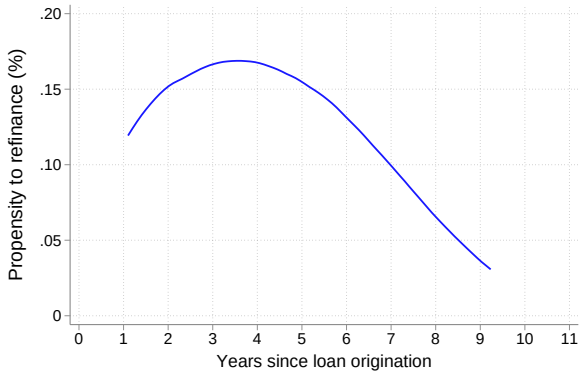
suited to isolating the effect of portability on its own. A cleaner assessment of that reform would require additional analysis.

Share of Borrowers Ever Refinancing. The previous results highlight that the likelihood that a borrower refinances its mortgage in any given month is low. We now leverage the length of our panel dataset to compute statistics on the extent to which a borrower ever refinances over a long period. In particular, we find that 89.4 percent of mortgage borrowers never refinance a mortgage during the 2012–2023 period we study, 9 percent refinance once, and 1.5 percent refinance more than once. These results may be partly driven by limited exposure, as some borrowers hold an outstanding mortgage during only part of our sample period. However, restricting attention to borrowers who hold an outstanding mortgage for at least five (ten) years within our sample period, still 87.7 (86.1) percent never refinance.[8] Taken together, these numbers indicate that mortgage refinancing is quantitatively limited even over long horizons.

[8]If we instead compute the same statistics at the level of borrowing spells, the results are similar: 91.7 percent of mortgages are never refinanced during our sample.

Figure 5: Refinancing over the life cycle of the mortgage

(a) Unconditional refinancing hazard



(b) Determinants of refinancing hazard

	Hazard Ratio
Origination spread (p.p.)	1.044**
	(0.020)
Change in spread by month t (p.p.)	1.248***
	(0.012)
Log borrower income	1.958***
	(0.051)
N	1,952,273

Notes: Panel (a) shows the unconditional probability of refinancing over time since loan origination, smoothed using an Epanechnikov kernel. Panel (b) reports results from estimating a hazard model for refinancing as a function of the spread between the interest rate and the TIB rate at origination computed as interest rate$_{ib0}$ − TIB rate$_{ib0}$, the change in the TIB rate over time computed as TIB rate$_{ib0}$ − TIB rate$_{ibt}$, and the logarithm of borrower income. We report exponentiated coefficients from a Cox hazard model, which should be interpreted as proportional shifts to the baseline refinancing hazard and are constant over time. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Refinancing as a Share of Originations. Figure 4 reports the composition of mortgage originations over time. On average, refinancing accounts for around fourteen percent of amount-weighted originations in our sample, whereas most mortgage market activity is concentrated in new borrowing and, to a lesser extent, in additional mortgages taken by borrowers who already hold an outstanding loan. Thus, Figure 4 makes clear that mortgage refinancing is a relatively minor component of gross origination activity in the Chilean market, consistent with previous findings in Banco Central de Chile (2019), which state that refinancing accounted for around eight percent of amount-weighted originations in the 2013–2019 period —our estimate for those years being larger, at about 15 percent, in part because our algorithms also capture cash-outs and refinancing across banks. The contrast with the United States is substantial. In that setting, refinancing accounts for a large share of mortgage flows. For instance, Freddie Mac (2020) reports that in the first quarter of 2020—when mortgage rates were at historically low levels—refinancing activity reached about 65 percent of all first-lien single-family mortgage applications in the United States. Figure 4 shows no comparable episode in Chile: even at its highest levels, refinancing did not exceed 25 percent of mortgage originations. Overall, these patterns suggest that mortgage market turnover in Chile is driven primarily by new borrowing rather than by the repricing or restructuring of existing loans.

Correlates of Mortgage Refinancing. Most economic models would predict that the decision to refinance depends on the balance between the gains from obtaining a lower rate and the costs

of refinancing the loan (Campbell and Cocco, 2003; Agarwal *et al.*, 2013). Figure 5 explores how refinancing varies over the loan's life cycle and with variables likely to affect the gains from refinancing. Figure 5-a shows that refinancing is more likely early in the life of the loan. This pattern is consistent with the fact that, at shorter durations, interest represents a larger share of the scheduled payment and, as a result, the present value of reducing the mortgage rate is correspondingly higher.

Beyond this time pattern of refinancing, we explore how it depends on contract covariates, economic conditions, and borrower characteristics. Figure 5-b shows results from estimating a hazard model for refinancing as a function of plausible refinancing drivers observed in our data. The results point in the expected directions. Refinancing is more likely when a mortgage was originated at a higher spread, since borrowers who got worse interest rates at origination (all else equal) have more to gain from subsequent declines in market rates and a greater scope to reduce their borrowing costs. This is consistent with prior evidence (Bhutta and Keys, 2016). In particular, an origination spread that is one percentage point higher is associated with a 4.4 percent higher refinancing hazard. Relatedly, we find that the refinancing hazard increases as this spread rises over the mortgage's life cycle (due to decreases in banks' funding rates). This effect is stronger: a one percentage point decrease in the funding rate increases the refinancing hazard by 25 percent. Finally, we find that borrower attributes also impact the likelihood of refinancing. In particular, a 10 percent higher borrower income is associated with a 6.6 percent higher refinancing hazard. This relationship could operate through a variety of mechanisms (e.g., higher income may correlate with financial education, better access to banking services, or others), which we are unable to explore with our data.

These results are consistent with the view that borrower-level refinancing behavior is shaped by a combination of mortgage contract terms, time-varying economic conditions, and borrower characteristics, and that borrowers respond with substantial heterogeneity to these drivers, as shown in Berger *et al.* (2021).

Refinancing within and across Banks. Table 3 also sheds light on whether refinancing occurs within the incumbent bank or through a switch to a different lender. Roughly one-fourth of the refinancing events we identify occur across banks, while the remaining three-fourths are refinanced within the same bank. Note that this split likely understates the true importance of cross-bank refinancing, since our procedures are less well-suited to detecting cash-out and cash-in refinancing across lenders. Still, because cash-out and cash-in refinancing account for a relatively small share of all detected events, the evidence points to a substantial home-bank advantage in the Chilean mortgage refinancing market. One interpretation is that switching lenders entails meaningful costs, including the need to establish a new lending relationship and to repeat operational steps such as reassessing the property and other collateral and processing the loan. This interpretation

is consistent with the broader mortgage literature emphasizing incumbency and relationship advantages for the home bank. For example, Allen *et al.* (2019) documents a sizable home-bank advantage in the Canadian mortgage market, which they interpret as reflecting search frictions and borrower loyalty. Looking ahead, one natural question is whether the financial portability reform reduced these switching frictions and increased cross-bank refinancing, which is a natural avenue for future research.

5 Discussion

Quantifying mortgage refinancing is a relevant input for policy, since refinancing has been shown to be an important element of mortgage markets by influencing the transmission of monetary policy to households and affecting the distribution of gains from lower interest rates. In this paper, we build on previous work to propose a set of practical algorithms for detecting refinancing events that can be implemented in settings where researchers observe standard mortgage borrowing stocks and originations but do not directly observe whether an origination is a refinancing event. Our results suggest that these methods are informative and can recover a meaningful share of refinancing activity from administrative data.

When applied to Chile, these methods reveal that mortgage refinancing is quantitatively limited in this setting. Understanding and quantifying the barriers to mortgage refinancing has received substantial attention in the household finance literature since Campbell (2006). Identifying the implications of policies that target these barriers for household borrowing costs and other outcomes in this market is an important area for recent and future research (Andersen *et al.*, 2020; Berger *et al.*, 2024), which the authors are currently studying in the Chilean market (Bhattacharya *et al.*, 2026).

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A Appendix: Implementation Details

When implementing our algorithms on real data, we must make choices about which observations to include as inputs and how to define key data objects and tuning parameters. Most often, our implementation choices are driven by reducing the impact of noise in the data and the amount of false positives when detecting refinancing events. Finally, we note that our specific choices naturally apply more directly to the Chilean market data, though similar choices would likely be required in other settings.

A.1 Data Preparation and Consolidation

Preparing Borrowing Stock Data. In the data, mortgage borrowing stocks are sometimes noisier than one would expect from regular repayment behavior. In addition, new originations and refinancing events are not always immediately recorded into the borrowing stocks dataset. As a result, loan balances occasionally disappear temporarily from the borrowing stocks data for a couple of months around a refinancing event. To guard against this, as well as against noise, we impute borrowing stocks for gaps of three or fewer consecutive months with zero observed balance within a borrowing spell by carrying the last observed positive balance forward. Relatedly, we set borrowing stocks below 3 UF (~US$137) to zero, mainly to avoid noise from a few borrowing stock series that remain at near-zero for long periods in the data.

Borrowing Spells. Borrowing spells are our proxy for individual loans in the borrowing stocks data—recall we only observe borrowing by individual at a given lender, rather than individual mortgages at a lender. In an attempt to track genuine mortgage loans rather than short-lived non-zero borrowing stock series, we require borrowing spells to be at least eight months long. This choice helps provide statistical power for the structural break tests implemented in the context of algorithm 3.

Jumps and Segments. We define a borrowing stock jump as a change in the borrowing stock, $|\Delta \ell_{ibt}|$, that exceeds the within-segment average by five standard deviations. Since segments are recursively defined by borrowing stock jumps, we identify them through a convergent iterating loop.

Consolidating Results. We exclude originations labeled as "reprogramming due to loan deterioration" from being detected as refinancing, and include into this group any origination with a zero-interest rate. We also filter originations under 100 UF (~US$4,500), which we consider too small to be true refinancing. To guard against the same event being flagged multiple times, whether by the same algorithm or across several algorithms, we group detected refinancing events that occur within 3 months of each other—chaining transitively as needed if there are several—and filter out all but the earliest refinancing flag. We find that 4 percent of detected events were flagged by more than one algorithm on this account, whether concurrently or in nearby months.

A.2 Algorithm 1

Parameter Choices. Under this algorithm, an origination is flagged as a refinancing event if the statistic in equation (1) exceeds the parameter $\bar{\kappa}$ in two or more of the T post-origination periods. We use a look-forward window T rather than checking the first post-origination month alone because, in a few cases, the borrowing stock data incorrectly add a refinancing-related origination before removing the previously held loan from the series, as shown in the example in Figure 2-a. In practice, we employ a look-forward window of $T = 4$ months and a threshold $\bar{\kappa} = 0.8$, where equation (1) must hold in at least $H = 2$ of them.

False Positive Filters. We attempt to prevent false positives, by excluding several mortgage originations from the procedure. First, we omit originations within four months of the end of the observed period, where we lack sufficient observations to compute the statistic. Second, we omit originations preceded by a borrowing stock jump without a matching origination flow in the prior four months, since that may indicate a new mortgage recorded with delay in the originations data rather than a refinancing event. Third, we omit originations at the start of a borrowing spell or within four months of the start, as these most likely reflect corrections to the initial origination rather than genuine refinancing events. Fourth, we omit originations with zero outstanding balance at or immediately after the origination date, as these cannot represent within-lender refinancing, which requires both a positive balance before and after the refinancing event.

A.3 Algorithm 2

Parameter Choices. First, we set $\gamma = 0.06$, which is a conservative upper-bound for closing costs. In addition, we set $\phi = 0.10$ and $\psi = 0.05$, which allow for minor discrepancies between the new origination amount and the observed borrowing stock while remaining overall stringent. The distribution of the number of flagged refinancing events that we detect is smooth around each cutoff. We employ the same H and T values as in algorithm 1, such that equations (3) and (4) must hold for at least 2 of the 4 months following the origination.

False Positive Filters. For cash-out refinancing specifically, we exclude transactions where either the prior outstanding borrowing stock or the origination amount falls below 200 UF, as our filtering conditions tend to fail at separating new loans from cash-out refinancing in the presence of low balances.

A.4 Algorithm 3

Preparation. This algorithm attempts to detect changes in the evolution of borrowing stocks. To ensure these tests capture changes in smooth amortization rather than discrete balance movements, we replace jumps in the $\Delta\ell_{ibt}$ by the average $\Delta\ell_{ibt}$ of their respective segment. We also take the three-period moving average of $\Delta\ell_{ibt}$, thereby eliminating noise and improving the break test

performance. The algorithm is run on individual borrowing spells of at least eight months, since a structural break test would lack sufficient power over shorter series.

Slope Break Test. The structural break test we consider requires a threshold for rejection of a constant slope in the borrowing stock. We consider a break statistically significant if the F-statistic exceeds $f^d = 2 \times 12.29 = 24.58$, which is twice the 95 percent asymptotic critical value of the Bai-Perron test. This conservative threshold is motivated by the limited statistical power of the test: borrowing spells contain at most 180 monthly observations. For the same reason, we do not search for multiple breaks. Moreover, breaks detected within the first 24 months of a borrowing spell are excluded, as these mostly capture the near-flat amortization curve early in a loan's life—compounded by noise—rather than genuine refinancing, which tends to occur in a mortgage's term.

Stock Break Test. The structural break test we consider also requires a threshold for rejection of a smooth level in the borrowing stock. When searching for a jump in the borrowing stock τ^s_{ibr} near the slope break, we apply an 8-month window ($T = 8$) on either side of the slope break, τ^d_{ibr}. A stock break in τ^s_{ibr} is then considered significant if the following two conditions hold. First, if the F-statistic exceeds $f^s = 100$.[9] Second, if the average stock in the four months after the break differs from the four months before by more than 10 percent and the absolute difference exceeds 300 UF. These proportional and absolute thresholds together guard against spurious detections at low balances, where small absolute changes can appear large in relative terms.

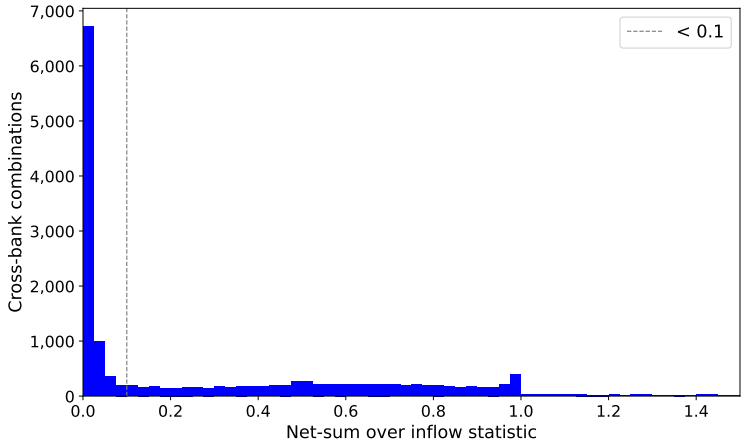
False Positive Filters. We take a few safeguards to prevent false positive refinancing events. First, a candidate refinancing is discarded if eight or more of the 12 post-break months fall within one standard deviation of the pre-break mean of $\Delta\ell_{ibt}$, indicating the post-break amortization is not meaningfully different from the pre-break series. Second, a candidate refinancing is also discarded when the average $\Delta\ell_{ibt}$ in the 12 months before or after the break is non-negative. That is, we restrict attention to reasonably well-behaved borrowing stock series with a decreasing borrowing stock around the break, which allows us to interpret the event more confidently as a refinancing rather than as some other shift in borrower behavior.

A.5 Algorithm 4

Parameter Choices. The role of the tolerance parameter η is to separate genuine refinancing events across banks from unrelated jumps in borrowing stock. After experimenting with a range of values, we set $\eta = 0.1$, because when taking all valid tuples of stock jumps that occur within λ

[9] This threshold is considerably higher than f^d because the stock level is trending over time, so any structural break produces a large F-statistic under a piecewise-constant data generating process. The threshold of 100 is a conservative heuristic to isolate genuine discrete discontinuities.

Figure 6: Distribution of tuple-level net sums



Notes: This figure shows the binned distribution of net sums over inflows—the statistic described in equation (5) and generalized in this Appendix—for all valid and unique stock jump combinations for our current choice of parameters, relaxing the η-constraint. The vertical line is our choice for η, which clearly captures the mass near zero.

months of each other,[10] the distribution of tuple-level net sums as in the left-hand side of equation (5) is bimodal, with a large mass close to zero and a long tail peaking near one, as displayed by Figure 6, our choice of η neatly separates the mass near zero, pointing to related jumps across lenders, from the rest of the distribution. In addition, the support for the integer λ in equation (5) is 0–4, that is, we set the forward search window for possible tuples to four months, which is somewhat less stringent than other parameter choices we adopt, yet it allows us to capture cases where flows across banks take longer to get recorded in the data. Moreover, the near-zero matching condition captured by η is highly restrictive, limiting the extent to which a loose search window may lead to misleading results.

General formula for equation (5)**.** To accommodate tuples with inflows and outflows across more than two lenders, we generalize equation (5) for an arbitrary number of lenders as:

$$\left| \frac{\sum_{(j,t)\in\mathcal{J}_i} \Delta\ell_{ij,t}}{\sum_{(j,t)\in\mathcal{J}_i} 1\{\Delta\ell_{ij,t} > 0\} \cdot \Delta\ell_{ij,t}} \right| < \eta$$

where $\mathcal{J}_i$ is the set of all lender-month pairs involved in the refinancing, and the denominator is the sum of all inflows.

Tuple Sizes. We do not feed the algorithm with specific bank tuples over which to search for refinancing events. Rather, the algorithm searches over all tuples of up to four jumps that occur within a 4-month window in the borrowing stock for a given borrower. In practice, however, no

[10] Valid tuples must contain at least one positive and one negative jump, such that they might net out to zero.

4-tuples are found in our data, and 3-tuples are rare. Additionally, we require that each individual borrowing stock jump in a tuple accounts for at least ten percent of either the total inflow or the total outflow of borrowing, to prevent larger tuples from matching on borrowing stock jumps of negligible amounts.

Tie Breaking. When the same borrowing stock jump appears for multiple candidate tuples within a borrower, we retain only the one with the shortest month span, hence prioritizing the most temporally concentrated match as the most plausible refinancing event. If we still have a tie, we randomize. This happens rarely in practice.

A.6 Sensitivity Analysis

The results from our algorithm depend on the choices of parameter fed to them. In this section, we study the sensitivity of some of our findings to those choices and provide some guidance based on the patterns of sensitivity. Figure 7 shows the main results for 14 different parameters across the four algorithms. We could classify these parameters into two categories: those governing refinancing detection itself ($\bar{\kappa}$, T, ϕ, ψ, γ, f^d, λ, η) and those that control false positive filtering.[11]

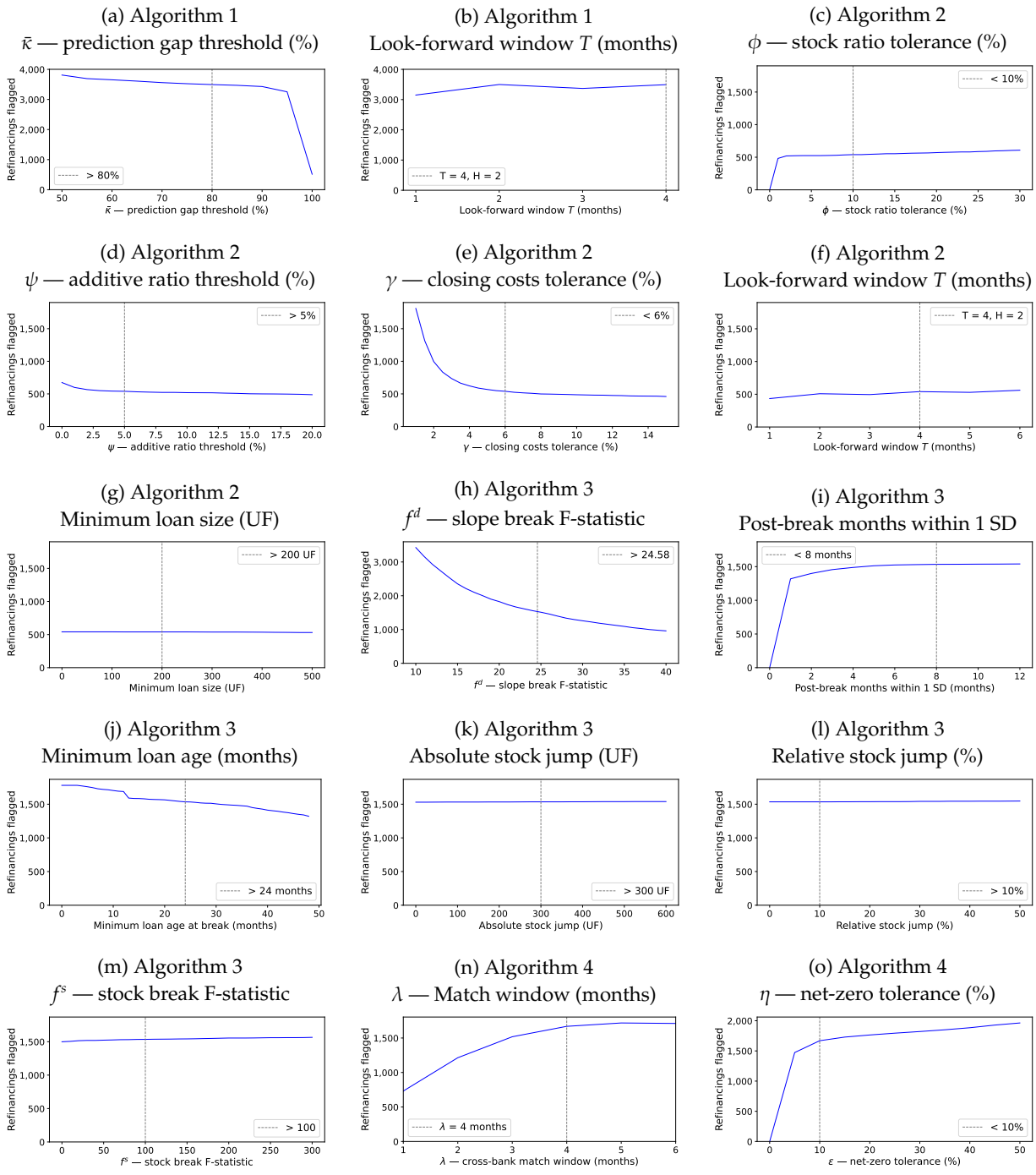
Among the parameters that govern the detection of refinancing events directly, there is at least one in each algorithm that could affect the number of flagged events substantially. For algorithm 1, that is the prediction gap threshold $\bar{\kappa}$, as shown in Figure 7-a). For algorithm 2, that is the tolerance to closing costs γ, as shown in Figure 7-e. For algorithm 3, that is the slope break F-statistic f^d, as shown in Figure 7-g. Finally, for algorithm 4, both the match window λ and the net-zero tolerance η are sensitive, as shown in Figures 7-n and 7-o. The choices for γ and η are well grounded, since closing costs of 4–6 percent are conservative but reasonable and yield similar results, and counts only begin to escalate at around 2 percent and below, where our confidence that the origination amount is *truly* above/below that of the baseline loan is reduced. The choice of $\eta = 0.1$ captures the set of jumps in borrowing stocks that are almost net-zero, with some tolerance for noise; choosing 0.05 or 0.2 would have delivered a similar count.

In the case of $\bar{\kappa}$ in algorithm 1 and f^d in algorithm 3, our parameter choices are more heuristic: although motivated by concerns about noise and statistical power, and corroborated through manual checks of detection cases at different values for their respective threshold, the specific chosen value is somewhat arbitrary, and the counts of flagged refinancing events vary non-trivially around it for both algorithms, which warrants some caution in interpreting our results.

Finally, among the parameters that govern false-positive filtering, our analysis suggests that none affects the number of flagged refinancing events in a meaningful way, and we include them only for thoroughness.

[11] This list is not exhaustive, as there are additional decisions we made regarding false positives which were not per se dependent on a parameter, and we also omit the search window for stock jumps around a slope break in algorithm 3 and other similar time frame dependent filters. Our sense is that none of these significantly affect results.

Figure 7: Sensitivity of detection counts to algorithm parameters.



Notes: Number of flagged refinancing events for each algorithm as the value of one of the detection parameters is unilaterally shifted. Total refinancing detections in blue. The vertical dashed line indicates our chosen parameter value. Panels (b) and (f) jointly graph values of T and $H = T/2$.



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