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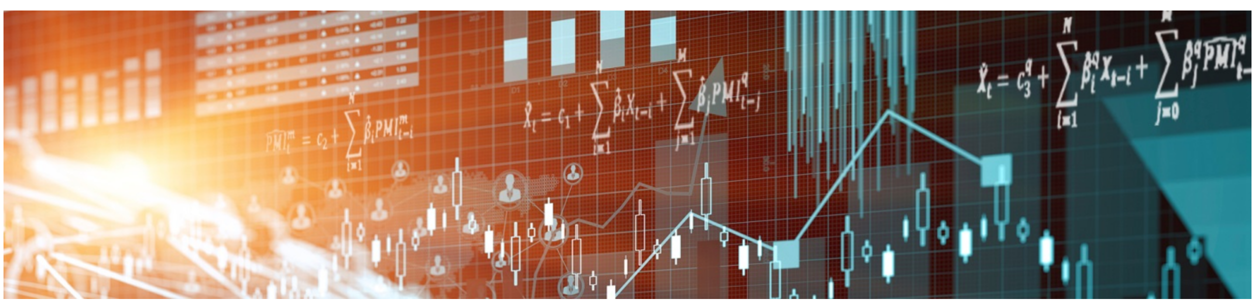

By Jean-Sébastien Fontaine, James Pinnington and Adrian Walton

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What Drives Episodes of Settlement Fails in the Government of Canada Bond Market?

by

Jean-Sébastien Fontaine,[1] James Pinnington[2] and Adrian Walton[3]

[1] Financial Markets Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
jsfontaine@bankofcanada.ca

[2] james.pinnington.jdp@gmail.com

[3] Financial Markets Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
awalton@bankofcanada.ca

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Abstract

We study settlement fails for trades in the Government of Canada bond market. We find that settlement fails do not occur independently. Using a novel and comprehensive dataset, we examine three drivers of fails. First, we find that fails are more likely following the release of surprise macroeconomic news. Second, settlement fails are more likely for bonds with greater trading activity in the borrowing market. These findings suggest that the recirculation of bonds through long settlement chains is important for understanding fails. Third, fails are more likely when interest rates are low and when the cost for borrowing a bond is high, which is likely because of frictions acting as constraints on the price to borrow a bond. Together, the evidence suggests that improvements to the price mechanism in the borrowing market could improve the recirculation of scarce bonds and may improve the functioning of the bond market.

Bank topics: Financial markets, Market structure and pricing, Payment clearing and settlement systems
JEL codes: E4, G1, G2, G21, L1

Résumé

Nous étudions les défauts de règlement sur le marché des obligations du gouvernement du Canada. Nous constatons que ces défauts ne surviennent pas de façon indépendante. À l’aide d’un nouvel ensemble complet de données, nous examinons trois facteurs à l’origine de ces défauts. Premièrement, la probabilité de défaut est plus élevée à la suite de la publication de nouvelles macroéconomiques inattendues. Deuxièmement, les défauts risquent davantage de toucher les obligations qui se négocient intensément sur le marché de l’emprunt. À la lumière de ces constats, la recirculation des obligations le long de longues chaînes de règlement se révèle un élément important pour comprendre les défauts. Troisièmement, les chances qu’un défaut ait lieu sont plus grandes lorsque les taux d’intérêt sont bas et que le coût d’emprunt d’une obligation est élevé, le défaut étant probable en raison de frictions agissant comme contraintes sur le prix d’emprunt. Ensemble, ces constatations donnent à penser que l’amélioration du mécanisme d’établissement des prix sur le marché de l’emprunt pourrait faciliter la recirculation des obligations présentes en quantité limitée et améliorer le fonctionnement du marché obligataire.

Sujets : Marchés financiers; Structure de marché et fixation des prix; Systèmes de compensation et de règlement des paiements
Codes JEL : E4, G1, G2, G21, L1

Non-Technical Summary

In financial markets, the exchange of cash and securities, "settlement," takes place with a delay following an agreement between two counterparties to trade. Commonly, a counterparty may not provide cash or securities in time for settlement and the trade is said to "fail." Market conventions permit settlement fails; when they occur, market participants almost always agree to attempt settlement again the following day, until settlement is successful. However, there is a debate about the relative costs and benefits of this convention. The history of fails in the Government of Canada bond market shows that fails occur episodically, concentrated in certain periods of time or in certain bonds. This indicates that fails do not occur simply at random, but are driven by market conditions.

The episodic nature of fails can be interpreted with the idea of "settlement chains." Often, delivery of securities for settlement of a trade will depend on receipt of securities from settlement of a different trade, and so on. This can happen when a trader has sold a bond not held in its inventory and buys, for example. When settlement chains are long, they are vulnerable to disruption since a single fail can break the chain, leading to many fails. Although we cannot directly observe these settlement chains, we can use historical data on bond-borrowing as a proxy. When a trader has sold a bond not held in inventory, it can borrow the bond from another trader at a cost. The number of such arrangements serves as a proxy for the length of settlement chains, since borrowing arrangements likely correspond to links in settlement chains.

Guided by past work, we focus on three conditions that may lead to fails: when macroeconomic news is released, when there is a high demand to borrow a bond, and when the cost of borrowing a bond is high. In each case, we find that the chances of a trade failing are higher. Our first finding may be explained by disruptions to settlement chains stemming from imbalances between buying and selling as investors trade on new information. Our second finding may be explained by demand to borrow bonds, leading to long settlement chains that are prone to disruption. Our third finding may be explained by the cost of failing being tied to borrowing costs. Previous work has shown that high borrowing costs or low interest rates may make an investor indifferent between borrowing a bond to settle or failing. Indeed, we find that historical borrowing costs are associated with fails and that the links between the bond-borrowing market and fails are stronger at low interest rates.

1. Introduction

Trades in bond and stock markets are typically settled with a delay ranging from a few hours, in the case of short-dated instruments, to a few days, in the case of longer-dated instruments. Settlement of trades means that securities are delivered against cash or other securities. For some trades, securities are not delivered at the expected settlement date. These settlement fails—or just "fails"—are common in bond and stock markets.

A debate persists around the relative costs and benefits of fails. For instance, constraints on settlement fails may restrict short-selling activities, which are important to support price efficiency and market liquidity (Liu, McGuire, Swanson 2016; Fotak, Raman, Yadav 2014). However, settlement fails can also be disruptive if they lead to a reluctance to trade or result in large, unanticipated outstanding counterparty exposures.

Our focus is different. We investigate the underlying determinants of fails in the fixed-income market, where there is little existing evidence. Preliminary evidence suggests that fails in fixed income are concentrated in the most liquid and largest issues, such as benchmark bonds, which we confirm in our data. This contrasts with the equity markets where the stocks of smaller and less-known companies are harder to borrow and may be more likely to have fails (D'Avolio 2002). Our analysis focuses on the Canadian government bond market where we can compile a unique and comprehensive dataset covering trades, settlements and fails, for both the bond and repo markets.

As a motivation for our analysis, we first test the simplest explanation for fails. Fails may be independent events, akin to accidents. In other words, each trade fails with a fixed probability, independently of other trades. This hypothesis is rejected in the data. Starting with observed trades, we generate a simulated distribution of failed trades using the assumption that each trade fails independently of others and with fixed probability. The simulated distribution of fails is different from the observed distribution. Days with very low volume of fails and days with very high volume of fails are much more frequent in the data than in our simulated distribution.

We investigate the determinants of fail episodes in the Canadian fixed-income markets. In all of our tests we include bond characteristics as control variables, such as the outstanding quantity, age, and benchmark status. Our focus is changes in the market conditions that may drive fail episodes. The evidence is consistent with fails cascading through "settlement chains." Settlement chains are formed when a bond can be recirculated through a series of transactions in the cash and repo markets. For instance, consider a short-seller who borrows a bond from a bond owner to settle a sale. The buyer in this transaction is now a bond owner who can again lend this bond—perhaps to raise funds for his purchase.

First, we find that the likelihood and the magnitude of settlement fails are larger following macroeconomic news releases. Economic news events are closely watched by bond investors and have a significant impact on bond yields. New information leads some bond owners to change their portfolio allocation. These purchases and sales, if widespread, may break links in settlement chains as bond lenders recall their loans to meet delivery obligations, increasing the chances of settlement fails. We find larger effects for negative economic news. Since negative news is typically associated with lower yields and higher prices, this is consistent with scarcity increasing the chance of settlement fails.

Second, we find that fails increase with trading activity in the borrowing market. The link between fails and the bond-borrowing market is also consistent with the existence of settlement chains. The details of these settlement chains are unobservable but they can be proxied using a bond's "velocity," where velocity is the amount of bonds on loan relative to the quantity of bonds available for trading.

Third, we find that fails increase with the cost of borrowing a bond, either on the securities lending market or the repo market. We also find that the sensitivity of settlement fails to borrowing activity and borrowing costs are larger when the level of interest rate is lower. Together, this evidence suggests that lower opportunity costs play a significant role in the likelihood and the size of fails. The opportunity cost from failing to deliver a bond is the forgone interest rate on the cash that is not received (when settlement fails). This opportunity cost decreases as the bond-specific borrowing cost increases and it also increases as the general level of interest decreases (e.g., see Fleming, Garbade 2005; Fontaine, Hately, Walton 2017).

The evidence suggests that the lower opportunity costs act as a friction preventing adjustments to the market price that would clear demand and supply of specific bonds.

Settlement chains provide a useful and intuitive way to interpret our results. But our findings do not depend on the existence of settlement chains. This is important since we do not observe settlement chains directly. We cannot tell whether a few fails affect one long and complex chain or whether many correlated fails affect several shorter, simpler chains.

Our results from the Canadian market may carry important implications for markets in other jurisdictions with similar institutional features. Several features of the Canadian government bond market are like other securities markets: market conventions for settlement fails; staggered settlement; the role of the repo market in borrowing bonds to settle short sales in fixed-income markets; and the cost of failing being tied to the level of interest rates.

One important question is whether market quality and allocational efficiency worsen for bonds with greater likelihood and magnitude of fails. We leave this for future research. Nonetheless, our results carry important implications for policy-makers. We find that the relationships between bond characteristics and fails have the expected signs. For instance, settlement fails are less likely for bonds issued recently or with larger issue. Nonetheless, fails happen more frequently on days with new economic information, when the level of interest rate is low and when a bond becomes expensive to borrow. This suggests that restoring the opportunity costs of fails can substantially reduce the likelihood and the magnitude of settlement fails, especially at times when investors are trading on economic news, or when interest rates are very low or negative. Indeed, restoring the price mechanism in the borrowing market via the introduction of a fails charge in the US market for Treasury and agency mortgage-backed bonds seems to have reduced fails (Fleming, Garbade 2005).

i. Related literature

Empirical work on fixed-income fails is limited. Corradin and Maddaloni (2015) find that central bank purchases are associated with fails in the Italian bond and repo market. Other existing results focus on equity markets, but these results neglect the role of economic news on fails. Boni (2006) shows that fails increase when borrowing fees increase. Higher levels of fails in the equity market may result in mispricing and increased volatility (Stratmann, Welborn 2012; Autore, Boulton, Braga-Alvesc 2014), but the evidence is mixed. Raising the costs of a settlement fail—to control the quantity of fails—may act as a constraint on short-selling and may reduce market liquidity and price discovery (Liu, McGuire, Swanson 2016; Fotak, Raman, Yadav 2014). Market-makers in equity options may also benefit from the possibility of failing and their associated costs affect option prices (Evans, Geczy, Musto, Reed 2005).

2. Settlement of transactions and settlement fails in the bond market

This section details the settlement of transactions in the Canadian bond market and, in particular, the events that occur when there is a settlement fail. This description is useful for understanding how fails happen.

i. Transaction settlement in the bond and repo market

In Canada, as in most bond markets, the settlement of cash fixed-income transactions is usually deferred until a few days after a trade is negotiated. To illustrate, the price and quantity of bonds to be exchanged are agreed at time t, but no exchange of bonds and cash occurs at time t. Instead, the seller will deliver bonds to settle the transaction in exchange for cash at time $t + 3$.[2]

In contrast, the repo market has a same-day settlement convention; trades are agreed and settled on the same day. Therefore, a seller in the cash market at time t can use the repo market to borrow the bond using a reverse repo transaction at time $t+1$, $t+2$ *or* $t+3$ to settle its transaction. One important benefit from deferred settlement in the cash market is that market participants may sell bonds that they do not hold in inventory at time t. For instance, a dealer

[2] By convention, settlement occurs at $t+3$ *f*or Government of Canada bonds with maturity greater than three years and at $t+2$ for bonds with maturity less than three years. Money market instruments including repos settle on the day of trade. As of 5 Sept 2017, Canadian and US markets moved to a $t+2$ settlement cycle for markets that weren't already settling at $t+2$ or earlier: www.cds.ca/newsroom?id=161.

may sell a bond to provide liquidity to a client or to establish a short position (to benefit interest rates rising) and then enter into repo transactions at later dates to obtain securities.

ii. Failure to deliver bonds during transaction settlements

But what happens if a short-seller or a market-maker does not deliver bond at *t+3* to settle the transactions? By design, the bond market does not stigmatize settlement fails. Instead, the counterparties can agree (and almost always agree) to delay settlement by one day, keeping the initial terms unchanged. Therefore, any capital gain or loss due to a change in yield is still computed relative to the time-*t* price. However, failing to deliver a bond still carries a cost: the party that fails to deliver securities does not receive cash and forgoes interest at *t+3*. The party delivering cash can keep the cash and earn interest until settlement is successful.

Settlement fails in repo transactions are handled similarly. Repo transactions specify a time and price at which bonds and cash must be exchanged. Again, failing to return the bond is not stigmatized. Both parties can agree to roll over the repo transactions by one day, but keep the initial terms unchanged. In this case, failing to deliver a bond has the opportunity cost of forgone interest rates.

3. Hypotheses

This section details three hypotheses at the core of the paper. These three hypotheses propose distinct economic determinants that increase the likelihood and magnitude of settlement fails. These determinants are also discussed in Fontaine, Hately and Walton (2017).

i. Economic surprises and settlement fails

Settlement chains are not static. At any point in time, investors—long or short—may choose to reverse their position. For instance, some long investors can decide to sell their bonds. To execute this sale, the investors must recall the bonds that they own but had lent. This forces their counterparts to search for bonds available for lending, which leads to Hypothesis *I*.

Hypothesis *I*

The likelihood and magnitude of bond settlement fails are greater following significant economic news surprises.

Investors assess the new information contained in economic surprises. Therefore, the surprises can lead to a large reallocation of bonds between buyers and sellers if the news leads them to reassess the value of their bond holdings. If a large number of sellers recall securities they have lent as a result of the information release (i.e., economic surprise), several links in settlement chains may be removed. To restore the settlement chain, the borrowers of bonds that face a recall must borrow again from another bond owner, or another set of bond owners. Hypothesis *I* predicts a larger likelihood that at least one recall will fail to settle and cascade through the settlement chains.

ii. The borrowing market and settlement fails

Bonds with relatively high trading volume in the cash market tend to have a large stock on loan (either via the repo or securities lending market; see, e.g., Bulusu, Gungor 2017). This happens mechanically, as market-makers and short-sellers borrow bonds to settle a large volume of cash market transactions. In turn, the buyer in the cash market can make this bond available for lending again. For instance, this buyer may use a repo transaction to finance the position. Because of staggered settlement (see section 1), the same bond can circulate through a chain of repo and cash transactions. This leads to our second hypothesis.

Hypothesis *II*

The likelihood and magnitude of bond settlement fails are greater for bonds with higher velocity.

The existence of settlement chains has an important consequence. Not all counterparties along settlement chains hold the bond in their inventory. The bond instead passes from one investor to another until it reaches its final owner. We refer to the length and number of settlement chains as a bond's velocity. Velocity captures the idea that the number of settlement claims can outnumber the quantity of bonds available for trading. When velocity increases, isolated fails can cascade through the settlement chain. Of course, it could be that there is no settlement chain. In this case, statistical tests should reject Hypothesis *II*.

Note that the velocity label is appropriate because of the similarities between fixed-income settlement and fractional-reserve banking. In the fixed-income market, the number of settlement claims on a specific bond may expand beyond the stock of bonds of the same issue available for trading. In the analogy, the quantity outstanding of a specific bond represents base currency and settlement orders represent demand deposits. Similar to how demand deposits are a multiple of base currency, settlement claims may outnumber available bonds. In this case, changes in the velocity of a bond make the bond supply elastic.

iii. Interest rates and settlement fails

An investor that fails to deliver bonds and misses the settlement of a transaction does not receive cash, implying that the investor forgoes the interest that could be earned on this cash. This is the opportunity cost associated with settlement fails. To attract a bond, an investor can offer to lend cash at a lower interest rate. The difference between this lower bond-specific rate and the more general interest rate, labelled the special spread, measures the cost of borrowing the bond.[3] But the lower interest rate offered in this transaction also implies that the opportunity of a fail has decreased, which leads to the following hypothesis.

Hypothesis *III.1*

The likelihood and magnitude of bond settlement fails are greater when the costs of borrowing a bond are higher.

The last hypothesis connects activity in the borrowing market to the level of interest rates. When the overnight interest rates are high, the opportunity cost is the most important cost from failing to deliver bonds.[4] When the overnight interest rate decreases, there is less room for the price of borrowing a scarce security to adjust and clear the market. All else being equal, a lower overnight rate makes the constraint on the price of borrowing a particular bond more

[3] In the repo market, a scarce bond is said to be "on special." Investors can attract scarce bonds as collateral by offering their counterpart a special rate that is lower than the GC rate. The difference between the GC and special rate is the borrowing fees for a particular bond on the repo market. See, e.g., Duffie 1995.

[4] There are other costs to settlement failures; for instance, reputational costs and regulatory capital costs. Large clusters of persistent fails make reputational costs largely irrelevant, since the attribution of the initial settlement fail is largely impractical. Anonymous trading via a repo CCP also reduces the role of reputational costs. In Canada, securities financing transactions are exempt from any capital charge related to settlement failure (Fontaine, Hately, Walton 2017).

likely to bind. Hence, we expect the relationship between fails and borrowing costs and as well as between fails and velocity to strengthen as the overnight rate decreases.

Hypothesis *III.2*

The relationship between fails and activity in the borrowing market is stronger when the level of the overnight interest rate is lower.

It is true that we should expect a more direct relationship between fails and the overnight rate, since the opportunity costs of settlement fails decrease with the level of interest rate (Fleming, Garbade 2005; Fontaine, Hately, Walton 2017). We do not test this direct channel since the variations of the overnight rate are not sufficient in our sample.

4. Bond data

We merge several sources to construct a panel dataset. Our sample runs from October 2014 to February 2017. The beginning of our sample is dictated by data availability. This period exhibits large variations in settlement fails, both across bonds and over time, which we describe below.

The unit of our dataset is bond-days. For each day, we identify the ISIN of all outstanding Government of Canada nominal bonds denominated in Canadian dollars using a dataset from Thomson Reuters. We ignore inflation-linked bonds owing to low trading volume. We ignore Treasury bills, since they are settled on the same date as they are traded. We then collect a rich set of market information about these bonds. Table 1 lists key variables and data sources, which we describe below.

Table 1: Description of variables.

Short name	Description	Unit	Source
Velocity	Securities on loan as a share of float	%	Markit
Borrowing Fee	Securities lending fee	Bps	Markit
Repo Spread	BoC target rate minus special repo rate	Bps	CDCC
Log Volume	Log daily settlement volume	Log-millions	CDS
Log Float	Log of float	Log-millions	Thomson Reuters
Age	Time since issuance	Years	CDS
GC	Bank of Canada target GC rate	Bps	Bank of Canada

Yield	Yield to maturity	%	DEX
Benchmark	Benchmark status dummy	[0,1]	Bank of Canada
Pre-benchmark	Pre-benchmark status dummy	[0,1]	Bank of Canada

i. Outstanding amount data

We collect data on bonds' outstanding amount from Thomson Reuters DataScope. We use the outstanding amount as a proxy for the quantity of bonds available for trading. We refer to the outstanding amount as the "float."

ii. Trade settlement data

We merge our universe of nominal bonds with two datasets from the Canadian securities clearing and settlement authority, the Canadian Depository for Securities (CDS). The first dataset is commercially available and contains settlement orders related to Canadian fixed-income securities. Each settlement order is generated by an underlying trade. For each trade, we collect the ISIN of the bond, the par value of the settlement order, and the planned settlement date and whether the trade generated the settlement order. Trades that were part of a repo are flagged; we refer to all non-repo trades as "cash trades."

In the case of a cash trade, we observe a single settlement order. In the case of a repo trade, we observe two settlement orders: the first order is for the initial exchange of securities for cash, and the second order represents the return of the bond in exchange for principal and interest. We refer to this dataset as the "trades" dataset.

iii. Settlement fails data

The second dataset from CDS contains information about settlement fails for each bond and for each day. Each record represents a settlement order that failed. For each settlement fail, we collect the bond ISIN, the par value to settle, the planned settlement date and whether the underlying trade was a cash or repo trade. We refer to this dataset as the "fails" dataset. Note that we can identify new versus old fails.[5] The data include settlement fails that appeared

[5] If the settlement fail date occurs after the planned settlement date, then this trade had failed on a prior date and failed again at a new delivery attempt. We deem the settlement failure an "old" fail in this case.

unresolved for long periods of time. We attribute these to data errors and we exclude observations of settlement fails that have been outstanding for more than five days.

iv. Settlement volume

We merge the trades and fails dataset by ISIN to compute the total par value of each bond due to be settled on each date. From the trades dataset, we observe all new settlement orders generated by trading activity. From the fails dataset, we observe past settlement orders that failed in the past and that will be attempted again. For each bond-day in our sample, settlement volume is the sum of new settlement orders and older failed settlement orders. We will refer to the terms “settlement volume” and “volume” interchangeably. The appendix details the construction of the settlement volume series.

iv. GC and special repo rates data

We collect data from the Canadian Derivatives Clearing Corporation (CDCC), which provides central clearing services for a segment of the Canadian repo market. The dataset includes trade-by-trade data on repo trades that are cleared through CDCC. The data include the accrued interest of each trade from which we compute the daily average specific repo rate for each ISIN. We also compute the specific repo spread by subtracting the specific repo rate from the Bank of Canada’s target overnight interest rate.

v. Bond yields

We collect data from the FTSE TMX on daily bond yields. The dataset provides end-of-day yields for each bond in our dataset, which are computed from daily information provided by fixed-income dealers. We ignore observations of yield with less than 30 days to maturity since they are sensitive to small deviations from the theoretical price.

vi. Securities lending data

We collect data from the Markit Securities Finance dataset. This dataset provides securities lending information. For each bond ISIN and for each day, we collect the total par value on loan. Our proxy for the velocity of a bond is the ratio of this quantity of bond on loan to the quantity of bond outstanding (i.e., the float). This share of the outstanding bond takes a value between 0 and 1 by construction. We also collect the average borrowing fee for new loans over the past three days, weighted by the par value of each security loan.

Table 2 reports summary statistics for key variables describing bond characteristics and pricing information.

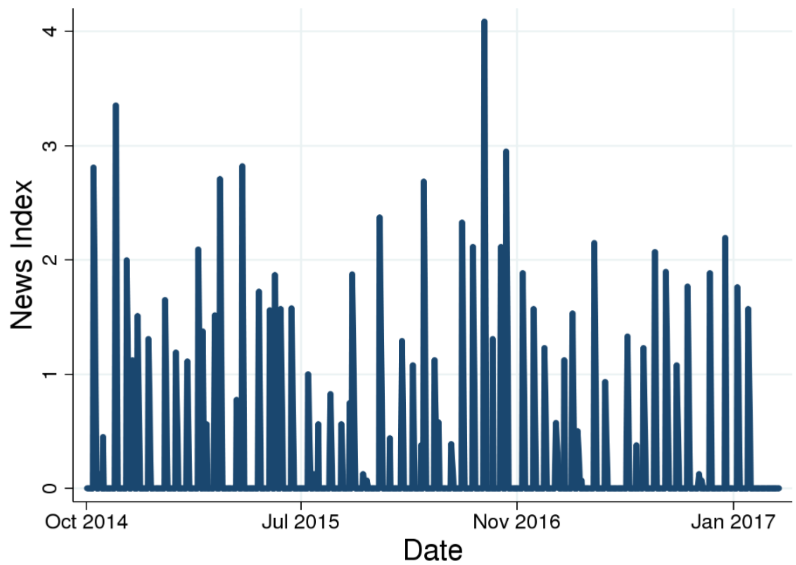
Table 2: Summary statistics—bond-level information.
The table shows summary statistics for bond-level variables over the sample period. The columns show the mean and standard deviation (*Mean* and *Std.*); 25th, 50th and 75th percentiles (*25%, 50%* and *75%*); and the number of observations (*N*). The results are split by benchmark and non-benchmark bonds across the upper and lower panels.

	Mean	Std.	25%	50%	75%	N
			Benchmark bonds			
Log Fails	4.15	2.40	3.00	4.66	5.80	939
Velocity	22.98	9.41	17.05	21.53	27.62	1787
Borrowing Fee	10.07	4.72	7.42	8.52	10.88	1777
Repo Spread	12.74	13.14	2.93	8.16	18.35	911
Log Volume	9.64	0.57	9.44	9.68	9.91	1785
Log Float	9.49	0.18	9.27	9.51	9.62	1787
Age	0.82	0.45	0.41	0.74	1.23	1787
Yield	0.99	0.43	0.62	0.88	1.34	1772
			Non-benchmark bonds			
Log Fails	2.32	2.69	0.40	2.71	4.48	5485
Velocity	11.53	7.44	6.73	10.51	14.47	25206
Borrowing Fee	10.43	5.92	7.30	8.65	11.86	20061
Repo Spread	9.56	11.39	2.04	5.68	11.38	9660
Log Volume	6.85	1.95	6.39	7.37	8.02	24185
Log Float	8.89	1.04	8.94	9.23	9.48	25206
Age	7.25	7.63	1.93	3.98	9.34	25206
Yield	1.04	0.58	0.57	0.83	1.41	24612

vii. Macroeconomic news

We construct an index of macroeconomic surprises. First, we collect the following economic releases: consumer price index (CPI), payroll survey, real gross domestic product (GDP), retail sales, and unemployment. Second, for each of these variables, we also obtain from Bloomberg the analysts' forecast and subtract it from the released data to compute the surprise component. Third, we normalize each variable to have a mean of 0 and a standard deviation of 1 on the days of their release. Our news index is the daily sum of the absolute normalized surprises. Implicitly, we assume each component of the index is equally important. Figure 1 reports this Canadian index of macroeconomic surprises.

Figure 1. Canadian macroeconomic news index.
Index of Canadian macroeconomic surprises for CPI, payroll survey, real gross domestic product, retail sales, and unemployment. We compute the surprise as the difference between each of the economic releases minus the corresponding survey forecast from Bloomberg, normalized to a standard deviation of 1. The macroeconomic news index is the sum of the absolute value of surprises.



5. Are settlement fails random?

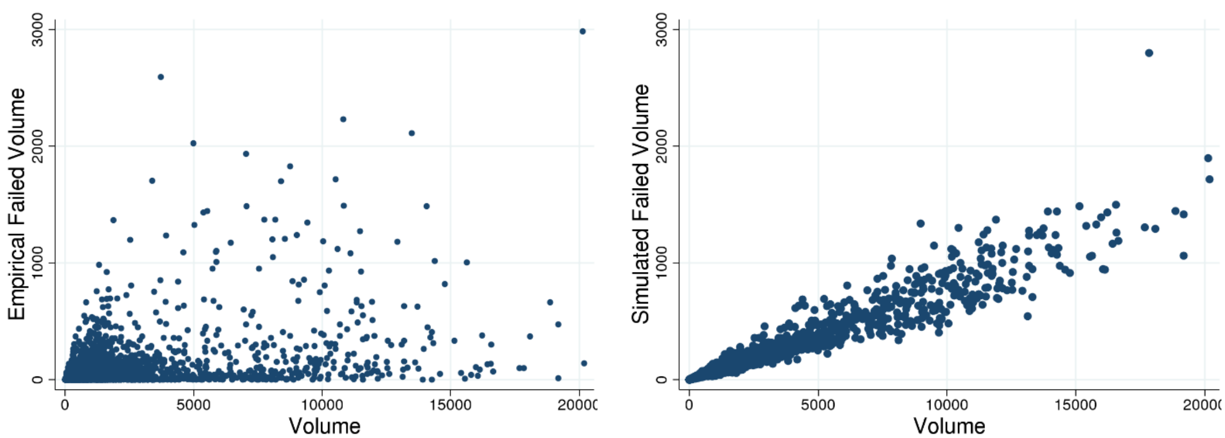
Could settlement fails be unrelated to each other? In other words, is it the case that a given trade may fail to settle with fixed probability, independently from any other trades? This is the simplest hypothesis. If this is the case, the volume of fails should be a constant proportion of the settlement volume (on average). This hypothesis can be tested with the following simulation. For each trade in our sample during the 2015 calendar year, we assigned a simulated failed variable taking values 0 or 1 with probability p or 1-p, respectively (i.e., a Bernoulli random variable).[6] The probability p is calibrated so that the empirical mean of the fraction of trading volume that fails matches the simulated fraction of trading volume that fails. Given that the simulated mean matches the observed mean, we can then ask whether the distribution also matches.

[6] We have used a subset of our sample dates in this case to balance the number of sample size with the computational ease of a smaller trade-by-trade dataset.

Figure 2 reports the volume of fails for each bond-day observation against the settlement volume: both observed fails (Panel A) and simulated fails (Panel B). These two distributions are very different. For any level of settlement volume (pick a point on the x-axis), the distribution of observed fails volume displays a cluster of small fails but with a fat tail of very large fails volume. In contrast, the distribution of simulated fails is tightly centred on the average fails volume. The simulated distribution does not fit the failed volume (i.e., it does not match the frequency of small, medium and large fails volume).

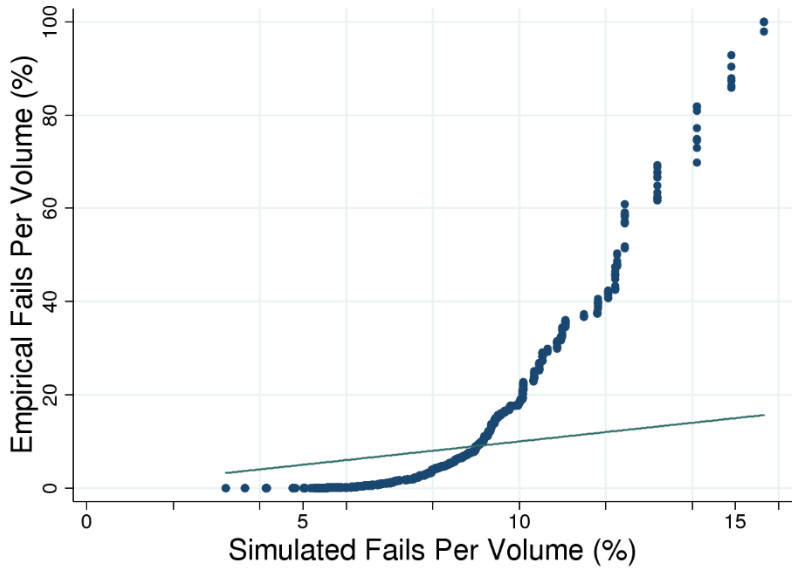
Figure 2: Empirical and simulated fails volume.
Fails volume and settlement volume for all trades in 2015 using actual data for fails and volume (Panel A) or using simulated data for fails from a binary random variable and actual volume data (Panel B).

Panel (A)—Empirical Distribution | Panel (B)—Simulated Distribution



We can also compare the empirical and simulated distribution of fails using a Q-Q plot. Figure 3 reports this Q-Q plot. The simulated distribution ranges from around 5% to around 15% of settlement volume that fails. This was already apparent in the right panel of Figure 2. Again, the empirical distribution is very different. For relatively small fail volumes, the quantiles from the observed distribution are much smaller. Very small fail volumes are much more likely in the data than in the simulation. This is consistent with “operational” fails that occur frequently but have little impact on other trades.

Figure 3: Q-Q Plot of empirical and simulated fails volume.



In contrast, for relatively large trades, the quantiles of observed fails are much larger than in the simulation simulated. For a significant number of bond-day observations, there is a large share of volume fails. Observed fails range as high as 100% of settlement volume.

Table 3 reports summary statistics for empirical and simulated data. The means are essentially the same by construction—close to 8%. However, a two-sample Kolmogorov-Smirnov test for equality of distribution functions yields a *p*-value of essentially 0, rejecting that the distributions are equal. The empirical distribution is very asymmetric. The median share of fails volume is 2%, much smaller than the mean. The tails are much larger, with kurtosis 16 compared with a kurtosis of 4 for the simulated distribution.

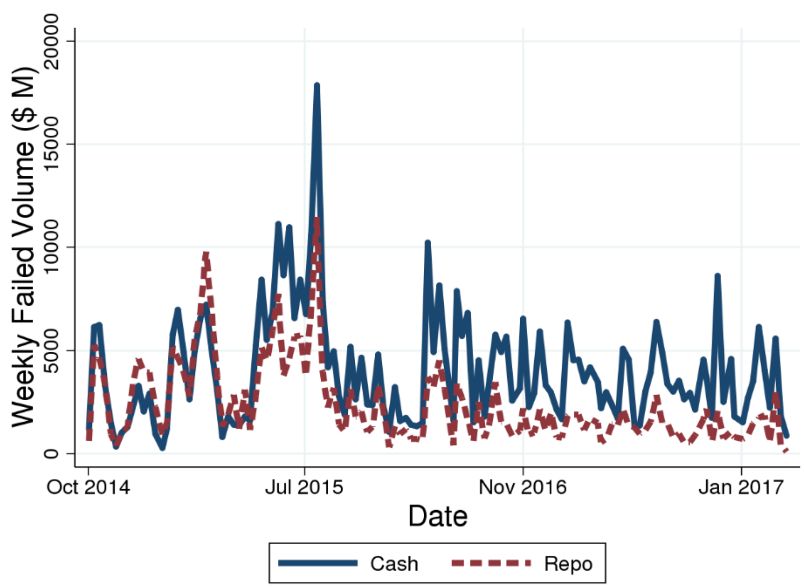
Table 3: Summary statistics for empirical distribution of fails.

	Mean	Median	Std.	Skewness	Kurtosis	N
Empirical	7.71%	2.31%	13.75%	3.31	16.37	1930
Simulated	7.77%	7.64%	1.93%	0.79	4.10	1930

Our findings are consistent with settlement chains from the recirculation of bonds driving the correlation between failed trades. Settlement chains explain why a small probability of fails for individual trade—the median share of volume that fails is less than 2%—can also explain cases where a large share of volume can fail on some bond-day. In some cases, settlement fails are highly correlated across trades.

The correlation is also apparent when we compare fails for repo and cash trades. Figure 2 plots fails separately for the cash and repo markets: these are highly correlated. This illustrates the recirculation between settlement of repo and cash market trades. Figure 1 also shows that the aggregate volume of fails alternates between periods with low and high quantities of fails. In fact, around 76% of bond-day observations exhibit no fails. This suggests that the challenge of explaining or predicting the volume of settlement fails should be separated into two: predicting between regimes with some fails or none, and predicting the volume of settlement fails (conditional on some fails).

Figure 4: Aggregated volume of settlement fails.
Weekly aggregated settlement fails in the cash and repo markets for Government of Canada nominal bonds in our sample (millions of Canadian dollars).



6. Determinants of settlement fails

To test hypotheses *I* to *III,* we perform two types of tests that are motivated by the observations from the previous section that fails for a given bond are not observed on most days, and that the failed volume varies widely when fails occur. In all of our tests, we include the age of a bond, the quantity outstanding and a dummy for benchmark bonds in our control variables.

Formally, we follow the two-stage approach proposed in Duan et al. (1983) for analyzing data with observations bounded below at 0. In the first stage, we use a logit model to consider the determinants of the likelihood that *any* fails occur on a bond-day observation. We consider fails in either cash or repo since they are highly correlated, as shown in Figure 4. In the second stage, we use linear ordinary least squares (OLS) to consider the determinants of the volume of fails, conditional on the event that *some* fails occur in a bond-day observation.

We estimate logit models of the following form:

$$failed_{i,t} = \begin{cases} 1 & if\ y_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$failed_{i,t} = \beta B_{i,t} + \alpha\, X_{i,t} + \gamma\, FE_i + \varepsilon_{i,t},$$

where $failed_{i,t}$indicates whether bond *i* exhibits at least one failed trade on day *t* ($y_{i,t} > 0$). $B_{i,t}$ is a vector of variables that varies depending on the hypothesis being tested, including: macroeconomic news surprises and yield changes (Hypothesis *I*); a bond's velocity (Hypothesis *II*); a bond's borrowing fee and repo spread (Hypothesis *III*.1); and the level of interest rates (Hypothesis *III*.2). The coefficient of interest is β. The set of control variables $X_{i,t}$ includes the logarithm of settlement volume for bond *i* on day *t*, its age, the float outstanding, and constant dummy variables indicating whether a bond is in the pre-benchmark or benchmark stage to control for bonds' life cycle effects. In all our results, the estimated coefficients for these control variables have the expected sign, although always statistically significant.

We estimate the magnitude of failed settlements, conditional on at least one fail, in a linear OLS model:

$$fail\ volume_{i,t} \middle| failed_{i,t} = \beta B_{i,t} + \alpha\, X_{i,t} + \gamma\, FE_i + \varepsilon_{i,t},$$

where $fail\ volume_{i,t}$ is the logarithm of bond i's total failed volume on day t. All other variables are as above; the coefficient of interest is β. In all regressions, we estimate panel models with bond fixed effects and we estimate standard errors clustered by bond and by date.

i. Economic surprises (Hypothesis I)

Hypothesis *I* predicts that economic surprises lead to a larger likelihood of fails and larger failed volume. We use a logit regression to model the likelihood that *any* fails occur on a bond-day observation and we use a linear OLS model to analyze the determinants of failed volume. The results support Hypothesis *I.*

Table 4 reports results for logit and OLS models where we include the contemporaneous news index and its first lag. Including only one lag is optimal based on the Bayesian information criterion. We estimate the models with and without control variates for robustness. The coefficients on certain control variates are suppressed for brevity. First, controlling for economic surprises, we find that velocity, specialness and volume are each significant determinants of the likelihood and magnitude of fails (this is discussed further in the following sections). Second, economic surprises significantly increase the likelihood of fails, but do not influence the volume failed (again, conditional on some fails occurring). Increased likelihood of fails is associated with *Lag News*, possibly because of hedging positions taken in the cash market before announcement dates that are due to settle after announcement dates. The coefficient estimates for *Lag News* are economically significant; the model indicates that when economic surprises range from their lowest to highest sample decile, the probability of a fail occurring the day after a surprise increases by around 10%, holding all other variables at their sample means.

Table 4: Economic surprises and fails.

Logit model for the likelihood of fails as well as OLS linear regression of fail volume with economic surprises. Every regression includes bond fixed effects. Standard errors are clustered by bond and date.

	(OLS 1)	(OLS 2)	(Logit 1)	(Logit 2)
News	0.0378	-0.0207	-0.0233	-0.0220
	(0.43)	(-0.29)	(-0.67)	(-0.58)
Lag News	0.136	0.0901	0.102***	0.124***
	(1.35)	(0.99)	(3.61)	(3.83)
Velocity		0.0254*		0.0168***
		(1.86)		(2.61)
Borrowing Fee		0.0426***		0.0183***
		(3.18)		(4.21)
Log Volume		0.435***		0.200***
		(5.35)		(3.18)
Controls	No	Yes	No	Yes
Obs.	6420	6084	26753	21615
Adj., Pse. R^2	0.151	0.200	0.115	0.093

Panel (A) of Table 5 reports results from an extended version of the model and includes bond-specific absolute value of change in yield on a day with economic surprises. The size of an economic surprise is an incomplete measure for its effect on the bond market. Other factors affect how investors respond to new information. The change in the yield of bond *i* following an economic surprise provides a more direct measure. As expected, the results are stronger when using a more direct proxy for the effect of news on yields. The evidence shows that a given bond is more likely to fail and that its failed volume is larger when its yield shows a larger change around economic news.

Table 5: Economic surprises, yield changes, and fails.

Logit model for the likelihood of fails as well as OLS linear regression of fail volume. The variable Diff|Y| is the change in the yield of bond i on date t (in absolute value) on a day with economic surprises. The variable Diff| Ŷ | is the predicted yield changes based on a regression of yield changes on surprises. Every regression includes bond fixed effects. Standard errors are clustered by bond and date.

Panel A—Regressions with actual yield changes				
	(Logit 1)	(Logit 2)	(OLS 1)	(OLS 2)
Diff |Y|	0.249	-0.0314	6.213*	2.506
	(0.12)	(-0.02)	(1.71)	(0.86)
Lag diff |Y|	4.589**	4.801***	11.35***	8.093***
	(2.54)	(2.63)	(3.65)	(2.83)
Controls	No	Yes	No	Yes
N	26753	21615	6420	6084
Adj., Pse. R^2	0.115	0.093	0.154	0.201

Panel B—Regressions with predicted yield changes				
	(Logit 1)	(Logit 2)	(OLS 1)	(OLS 2)
Diff | Ŷ |	-2.066	-3.946	13.56	6.570
	(-0.37)	(-0.68)	(1.11)	(0.71)
Lag diff | Ŷ |	20.87***	20.14***	20.96	13.89
	(4.32)	(4.12)	(1.64)	(1.30)
Controls	No	Yes	No	Yes
N	26753	21615	6420	6084
Adj., Pse. R^2	0.115	0.094	0.152	0.200

One concern with Panel (A) is that part of the results may be owing to fails causing yield changes (in addition to economic surprises causing fails). The observation that *lagged* yield changes explain fails should help to alleviate this concern. In addition, we can proceed with a two-stage estimator in the following way. In a preliminary step, we project yield changes on contemporaneous economic surprises, where we also include control variables about bond characteristics and trading activity. In the second step, we use the absolute value of the predicted yield changes in the regressions.

Panel (B) of Table 5 reports the results. The evidence provides two messages. First, yield changes that can be attributed to economic surprises are associated with a greater likelihood of fails. The coefficient estimates are larger and statistically significant. Second, predicted yield changes are also positively associated with failed volume but the estimates are not statistically significant.

For the OLS model of expected fails volume, we can modify our approach to obtain a two-stage least squares (2SLS) instrumental variable regression where we use economic surprises as instruments to estimate the effect of yield changes on fails. We split economic surprises between good and bad economic news. Positive inflation, retail sales or payroll surprise news as well as negative unemployment surprises are considered good economic news.

Table 6 reports the results of the 2SLS approach. Panel (A) reports results from first-stage regressions of yield changes on either the positive or the negative component of economic surprises. These regressions are estimated including controls for the other component of economic surprises; we include the negative component of economic surprises in the regression when we are interested in the positive component of economic surprises and vice versa.[7] The first two specifications (corresponding to the positive component of economic surprises) have Kleibergen-Paap F-statistics of around 4, indicating we cannot reject the null hypothesis that these are weak instruments. However, third and fourth specifications (corresponding to the negative component of economic surprises) have Kleibergen-Paap and Cragg-Donald F-statistics of greater than 15, allowing us to reject the null hypothesis that the maximum relative bias of our instrumental variables regression is greater than 10%. Individually, negative CPI and GDP surprises have significant coefficient estimates. Payroll and Unemployment have insignificant coefficients, but these data are released on the same day. Panel B reports results from the second-stage regressions of fail volume. The coefficient estimates have a magnitude similar to the results shown in Table 5. In addition, the estimates for negative news surprises are economically and statistically significant. A one-standard-deviation change in yield predicted by a negative economic surprise results in an increase in settlement fails in a single bond by around $40M when failed volume is at its sample mean and conditional on a fail occurring.

Overall, the evidence in Tables 4 to 6 supports our main message: economic surprises cause an increase in the likelihood of settlement fails. The fact that negative economic surprises appear

[7] Note that we account for the fact that payroll and unemployment are released on the same day. For instance, in a regression where the parameters of interest include the coefficient for positive payroll and unemployment surprises, we also include any negative payroll and unemployment surprises as control variables.

more important should be interpreted with care, since our sample is relatively short in the time-series dimension. Nonetheless, it is reassuring that the effect of news is more perceptible when bonds become more expensive; that is, when they are more difficult to find.

Table 6: The effect of yield changes on fail volume—instrumental variable regressions.
Instrumental variable regressions of fail volumes (conditional on positive fail volume) on yield changes using economic surprises as instruments. First-stage regressions (Panel A) with and without bond-level controls. Second-stage regressions (Panel B) with and without bond-level controls.

	Panel A—First stage			
	Positive surprises	Positive surprises	Negative surprises	Negative surprises
CPI	0.00657	0.00644	0.0157***	0.0168***
	(1.13)	(1.25)	(2.87)	(3.17)
Payroll	0.0155	0.0160	0.00554	0.00526
	(1.49)	(1.46)	(0.58)	(0.54)
GDP	-0.00354	-0.00325	0.0270***	0.0264***
	(-0.21)	(-0.20)	(6.42)	(5.89)
Retail Sales	0.0146***	0.0152***	0.00812*	0.00765*
	(2.80)	(3.31)	(1.82)	(1.88)
Unemployment	0.00741	0.00758	0.00331	0.00287
	(0.79)	(0.81)	(0.58)	(0.51)
Controls	No	Yes	No	Yes
N	26061	21070	26061	21070
Adjusted R^2	0.015	0.023	0.015	0.023

	Panel B—Second stage			
	Positive surprises	Positive surprises	Negative surprises	Negative surprises
Lag diff $\hat{Y}$	5.681	0.905	-17.63*	-19.88***
	(0.63)	(0.12)	(-1.76)	(-2.65)
Controls	No	Yes	No	Yes
N	6263	5958	6263	5958
Adjusted R^2	-0.016	0.065	-0.073	-0.018

ii. Explaining fails/no fails regimes (Hypotheses II *and* III.*1)*

Table 7 reports results for logit regressions. Hypothesis *II* predicts that the likelihood of settlement fails increases with a bond's velocity. Hypothesis *III.1* predicts that the likelihood of fails increases with borrowing costs. The evidence supports these predictions using either the borrowing fee or the repo spread as a proxy for the cost of borrowing a bond.

The results include coefficient estimates for velocity and borrowing costs with and without controls for bond characteristics (i.e., age, issue size). Higher velocity or higher borrowing costs increase the likelihood of settlement fails, either individually or combined with other controls. The estimated effect of each variable is significant both statistically and economically. Using the repo spread as a proxy for the costs of borrowing a bond reduces the sample size by half owing to limited data, but the coefficient estimate is higher and has greater statistical significance.

Looking at the other coefficients, we find that bonds with larger trading volume are more likely to fail. The age of a bond and the indicator for benchmark bonds also predict that fails are more likely with significant estimates. In other words, for non-benchmark bonds, older bonds are more likely to fail. The results show that the coefficients on issue size (float) are not significant. In other words, controlling for indicators of scarcity and velocity, the issue size does not help predict fails.

These results do not provide causal evidence between fails and velocity, but describe bond-specific conditions that are associated with fails. We do not investigate multivariate time-series dynamics.

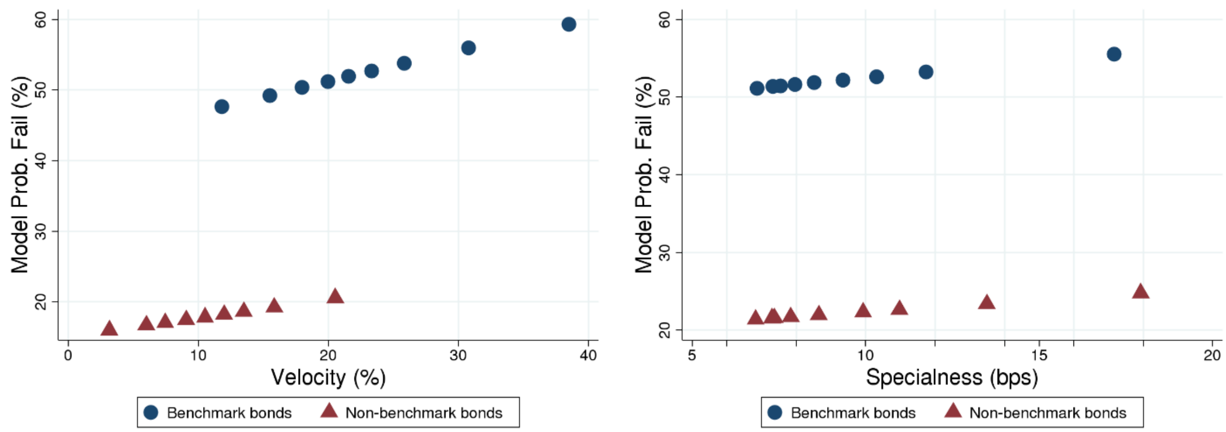
Table 7: Fail/no fail regimes, velocity and borrowing costs.
Logit regressions of the $failed_{i,t}$ indicator with value 1 when bond i exhibits at least one failed trade at date t; including bond fixed effects. Standard errors are clustered by bond and date.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Velocity	0.036***			0.0176***			0.0166***	0.0214**
	(4.82)			(2.59)			(2.59)	(2.22)
Borrowing Fee		0.0159***			0.0171***		0.0182***	
		(3.28)			(3.95)		(4.20)	
Repo Spread			0.0347***			0.0336***		0.0333***
			(7.17)			(8.52)		(9.02)
Log Volume				0.141**	0.207***	0.286***	0.201***	0.283***
				(2.17)	(3.34)	(3.87)	(3.22)	(3.96)
Log Float				0.447	0.321	0.191	0.243	0.126
				(1.64)	(1.11)	(0.51)	(0.91)	(0.35)
Benchmark				0.497***	0.565***	0.419***	0.442***	0.376
				(2.75)	(3.14)	(1.77)	(2.60)	(1.52)
Pre-Benchmark				-0.175	-0.224	-0.318	-0.253	-0.250
				(-0.44)	(-0.61)	(-0.67)	(-0.72)	(-0.52)
Age				0.0912	0.185**	0.307***	0.161**	0.334**
				(1.07)	(2.46)	(2.07)	(2.06)	(2.34)
N	26813	21717	10551	25927	21657	10551	21657	10551
Pseudo R^2	0.120	0.076	0.095	0.118	0.092	0.109	0.093	0.110

Figure 5 illustrates the results of the model specified in columns (4) and (5) of Table 4. The figure shows model-implied probabilities of fails for sample deciles of our variables of interest, velocity and specialness. For example, the first sample decile for velocity for benchmark bonds is around 12%. Evaluating the fitted logit model at this value and the sample means of all other variables yields a probability of at least one fail of around 48%. The results are economically significant. The model estimates indicate that when velocity changes from the lowest sample decile to the highest, the probability of a fail increases by around 12% for benchmark bonds and by around 5% for non-benchmark bonds, keeping all other variables at their sample means. For specialness, model estimates indicate that an increase from the lowest sample decile to the highest increases the probability of a fail occurring by around 4% for benchmark bonds and by around 3% for non-benchmark bonds, keeping all other variables at their sample means.

Figure 5: Model probability of a fail occurring.
The figure shows model values for the probability of a fail occurring in either the cash or repo market. Panel A corresponds to the model fit in specification (4) in Table 4, and Panel B corresponds to the model fit in specification (5) in Table 4. Points on the graph represent the probability of fails implied by the model when varying velocity (Panel A) or specialness (Panel B). The model is evaluated at each sample decile of velocity and specialness, holding all other variables constant at their sample means. Results are split into benchmark and non-benchmark bonds.

Panel (B)—Velocity	Panel (B)—Specialness



iii. Explaining fails volume (Hypotheses II *and* III.*1)*

Table 8 reports the results of benchmark OLS regressions of fails volume on velocity, proxies for borrowing costs and other controls. Hypothesis *II* predicts that failed volume increases with a bond's velocity. Hypothesis *III.1* predicts that failed volume increases with borrowing costs. The results show that velocity and borrowing costs predict larger fails volume. As in the logit model, these results do not provide causal evidence, but rather bond-specific conditions associated with fails. The results are significant economically and statistically. Model specifications (1) and (4) indicate that a one-standard-deviation increase in velocity results in an increase in failed volume for a single bond by around $20M when failed volume is at its sample mean and conditional on a fail occurring. Model specifications (2) and (5) indicate around the same magnitudes for a one-standard-deviation increase in the borrowing fee.

Among other controls, bonds with larger trading volume have larger fails volume. In contrast with the results for fails likelihood, the age of a bond predicts that fails volume is lower on average for older bonds. The coefficient on velocity becomes insignificant when using repo spread, but this is partly owing to the smaller sample. The issue size has the right sign but the coefficient estimates are not significant.

Table 8: Fails volume, velocity and borrowing costs.
OLS linear regressions of log fails volume for bond *i* at date *t*. Every regression includes bond fixed effects. Standard errors are clustered by bond and date.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Velocity	0.0336*			0.0243*			0.0260*	0.00763
	(1.69)			(1.73)			(1.92)	(0.38)
Borrowing Fee		0.0558***			0.0408***		0.0426***	
		(3.71)			(3.03)		(3.20)	
Repo Spread			0.0513***			0.0435***		0.0434***
			(6.91)			(6.21)		(5.15)
Log Volume				0.480***	0.448***	0.770***	0.433***	0.768***
				(5.77)	(5.86)	(6.66)	(5.31)	(6.65)
Log Float				-0.753	-0.617	-0.396	-0.689	-0.410
				(-1.41)	(-1.08)	(-0.60)	(-1.30)	(-0.64)
Benchmark				0.130	0.409	-0.401*	0.222	-0.414*
				(0.45)	(1.40)	(-1.66)	(0.84)	(-1.66)
Pre-Benchmark				-0.738	-0.688	-0.479	-0.703	-0.446
				(-0.93)	(-0.88)	(-0.77)	(-1.01)	(-0.73)
Age				-0.528***	-0.408***	-0.0731	-0.464***	-0.0635
				(-4.83)	(-3.87)	(-0.30)	(-4.32)	(-0.27)
N	6424	6088	2832	6424	6088	2832	6088	2832
Adjusted R^2	0.156	0.147	0.225	0.214	0.197	0.255	0.199	0.255

iv. The level of interest rates (Hypothesis III.*2)*

Hypothesis *III.2* predicts that likelihood and the magnitude of fails are larger when interest rates are lower. Unfortunately, the variations of the target rate are small in our sample. The Bank of Canada target for the overnight rate covered only three values: 1%, 0.75% and 0.50%. Therefore, we expect our tests to have small statistical power, since the variations in opportunity costs of fails can be swamped by noise in the regression. The variations are also infrequent. With only two changes in our sample, the changes in the GC rate can be swamped by other slow-moving factors that affect market conditions (e.g., time-trend). Because of these limitations, the following results can be seen as conservative.

As above, we estimate logit and OLS models for the likelihood and the magnitude of fails, respectively. To test the effect of the overnight rate, we implement the following modifications. First, we restrict the sample to observations before 1 January 2016 to balance the number of observations across different values of the GC rate. Second, we introduce the product of Velocity with the GC rate as an interaction variable. We expect a negative coefficient: the likelihood and the magnitude of fails should be more sensitive to velocity when the GC rate decreases. Similarly, but in separate models, we introduce the product of borrowing cost proxies with the GC rate as interaction variables. Again, we expect coefficients to be negative. In all cases, we also include the level of the target rate among control variables.

Table 9: Sensitivity of fails to velocity, specialness and the level of interest rates.
Logit model for the likelihood of fails as well as OLS linear regression of fail volume including the interaction of key variables with the GC target rate. Every regression includes bond fixed effects. Standard errors are clustered by bond and date.

	(Logit 1)	(Logit 2)	(Logit 3)	(OLS 4)	(OLS 5)	(OLS 6)
Velocity *x* GC	-0.0835**			-0.0101		
	(-2.44)			(-0.12)		
Borrowing Fee *x* GC		0.0378			-0.101**	
		(1.27)			(-2.14)	
Repo Spread *x* GC			-0.0389**			-0.125***
			(-2.21)			(-4.52)
Velocity	0.0842***			0.0269		
	(2.91)			(0.44)		
Borrowing Fee		-0.0144			0.116***	
		(-0.68)			(3.28)	
Repo Spread			0.0643***			0.141***
			(4.36)			(5.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13747	11390	10551	3121	2933	2832
Adj., Pse. R^2	0.126	0.103	0.110	0.264	0.242	0.264

Table 9 reports the results. Looking at the interaction variables, five out of six estimates have a negative sign, as expected, and four out of six estimates are statistically significant. A one standard deviation of velocity has different effects on the likelihood of fails as the GC rates decrease. With all variables at their sample means, the probability increases by around 11% when GC is 1%, but the probability increases by 13% when GC is 0.5%.

These results provide further evidence on the sensitivity of fails to the level of interest rates. This adds to the evidence provided in Tables 7 and 8, which links fails to borrowing costs.

7. Conclusion

Our results yield important messages. Fails are more likely and are greater in magnitude when a bond is more expensive to borrow. Fails are also more likely when a bond's velocity is larger—that is, when many buyers and sellers must meet to manage their exposures to bonds—and around the release of significant economic information. This suggests that fails happen at the worst of times since economic surprises coincide with times when investors have strong needs to rebalance their portfolios. The likelihood and magnitude of fails are more sensitive when interest rates are lower. This confirms that the frictions that act as constraints on the price mechanism make fails more likely, and suggests that restoring the price mechanism in the borrowing market when rates are low could be beneficial. In addition, improvements to the settlement procedure could be beneficial. For example, in Europe, some central clearing houses automatically source bonds clearinghouse members when fails occur, mitigating search frictions (Fontaine, Hately, Walton 2017).

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Appendix 1: Construction of volume series

Trades that fail to settle today are due to be settled the next trading day. Therefore, for each day in our sample, the settlement volume includes new trades and the previous day's failed settlements:

$$Total\ volume_t = New\ settlements_t + Failed\ settlements_{t-1}$$

We compute each term of the sum separately. From the trades dataset, we have records of new settlement orders generated by new trades. Aggregating all trades by settlement date (and not by trade date), we compute new settlement volumes for each bond-day in our sample. We provide a hypothetical example in the table below. Each record represents a new settlement order generated by a new trade. Note that there are two settlement orders for Trade ID 3. Because it is a repo trade, there is one order for the initial sale of securities and one order for the return (repurchase) of securities.

ISIN	TradeID	Trade type	Trade date	Settlement date	Par value
ABC	1	Cash	May 1	May 3	100
ABC	2	Cash	May 1	May 3	200
ABC	3	Repo	May 3	May 3	500
ABC	3	Repo	May 4	May 4	500
ABC	4	Cash	May 2	May 4	400

For each bond, we aggregate these trade records to produce:

ISIN	Settlement date	New settlement volume
ABC	May 3	800
ABC	May 4	900

Using the fails dataset, we then take the sum of all failed settlements per bond-day in our sample, aggregating by fail date. We provide a hypothetical example below. Each record represents a settlement failure for a single trade (in the case of a cash market trade) or a single leg of a trade (in the case of a repo market trade). In this particular example, the repo market settlement failure on May 4 indicates that the counterparty has failed to return bond ABC exchanged as collateral in a repo trade initiated on May 3.

ISIN	TradeID	Trade type	Trade date	Settlement date	Fail date	Par value
ABC	1	Cash	May 1	May 3	May 3	100
ABC	3	Repo	May 4	May 4	May 4	500

Aggregating all settlement failures per bond-day, we compute:

ISIN	Fail date	Failed volume
ABC	May 3	100
ABC	May 4	500

Combining the aggregated trades dataset and the aggregated fails dataset, we have:

ISIN	Date	New	Failed	Prior day's failed	Total volume
ABC	May 3	800	100	0	800
ABC	May 4	900	500	100	1000
ABC	May 5	0	0	500	500