Securities Portfolio Management in the Banking Sector*

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Abstract

We develop a method to measure securities selling activity by banks using publicly available data from regulatory filings. Using this data, we document stylized empirical facts and establish key relationships with other bank-level outcomes. Specifically, we find that contemporaneous changes in short-term liabilities (particularly deposits) are the factors most associated with selling decisions, but initial cash holdings and changes to bank capital or loans are also important. We use machine learning techniques to assess the extent to which bank security sales can be predicted out-of-sample and which ex ante factors are important in doing so. Despite substantial improvements, we find that predictability is limited. Overall, our findings suggest that structural models of fire sales in the banking sector should consider both funding and asset shocks. Additionally, our model estimates could be used (1) to measure and monitor the risk of indirect contagion and (2) to forecast bank selling within regulatory stress testing exercises.

Keywords: indirect contagion, systemic risk, macroprudential supervision

*This draft is preliminary and comments are welcome.

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1 Introduction

Following the 2008 Financial Crisis, researchers and policymakers became increasingly concerned about systemic risk in the financial system stemming from financial fire sales by banks. This concern was borne out of the belief that large volumes of financial asset sales in late 2008 combined with sharp declines in market prices further weakened financial institutions when they were already in distress (see, e.g., Brunnermeier, 2009; Laux and Leuz, 2010). As a consequence, researchers worked to develop structural models of financial asset fire sales (Coen, Lepore, and Schaanning, 2019; Cont and Schaanning, 2017, 2019; Cont and Wagalath, 2013, 2016; Duarte and Eisenbach, 2018; Greenwood, Landier, and Thesmar, 2015; Kirti and Narasiman, 2017; Rosen, 2019). In addition to providing theoretical insights into fire sale behavior and outcomes, a few of these models are also intended to be estimated using publicly available balance sheet data so that regulators can quantify and monitor the risks from "indirect contagion" in the banking system (i.e., potential system-wide losses that would propagate through financial fire sales).

Despite the growth in structural models, there is relatively little empirical evidence on the causes and factors associated with security sales by banks. As such, it is difficult to assess whether these models accurately portray bank behavior. Some models assume that selling is driven purely by binding leverage constraints while others allow for multiple potential binding constraints. Moreover, models differ in their assumptions regarding liquidation strategy in terms of both asset selection and speed of adjustment. The most commonly cited empirical paper is Adrian and Shin (2010), who show that banks manage book leverage to offset asset value shocks, as a justification for leverage targeting. Additionally, Duarte and Eisenbach (2018) provide empirical evidence that banks target their leverage and provide estimates of their speed of adjustment. Otherwise, the behavior of banks in the structural models mentioned above are based on assumptions.

In this paper, we aim to fill this empirical evidence gap by studying observed bank sales of securities in the data. To do so, we develop a method to measure securities selling activity by banks using publicly available data from regulatory filings. This method relies on the fact that banks are required to report both book values and market values for the bulk of their securities holdings. Our analysis proceeds in three broad steps. First, we document a set of stylized empirical facts regarding bank selling. Second, we establish empirical relationships between selling and other bank-level outcomes in order to better understand the factors associated with bank selling. Third, we use machine learning techniques to assess the extent to which bank security sales can be predicted out-of-sample and which ex ante factors are important in doing so.

In the first step, we document several stylized facts about security sales in the banking industry. We observe that the banking sector as a whole tends to be a net purchaser of securities in most quarters with a few key exceptions (e.g., during financial distress in 2008). When banks do sell securities, they tend to only sell safe securities. However, there are numerous cases in which a bank chooses to primarily sell risky securities instead. This observation prompts us to separately analyze the sale of risky securities in our formal empirical analysis. In terms of losses associated with aggregate selling activity, unrealized losses (i.e., declines in the market value of securities held on balance sheet) can be quite large, reaching 10% of bank capital in 2008.

In the second step, we perform an in-sample regression analysis to establish key bank-level factors associated with observed bank selling activity. We are careful to use the word "associated" because we do not rely on an identification strategy to isolate exogenous shocks, and therefore we cannot rule out reverse causality or unobserved confounding factors to explain our findings. Nonetheless, we believe that this analysis deepens our understanding of bank selling activity by identifying key empirical relationships and corresponding magnitudes. First off, we find that measures of changes in short-term liabilities (particularly deposits) contribute to the majority of our explanatory power from a regression perspective. Moreover, the signs of the coefficients are negative, which aligns with the theory of short-term-creditor-induced fire sales. Second, we find that declines in tier 1 capital are associated with security sales. This finding supports the view that regulatory capital constraints can incentivize asset sales and the view that banks will sell to return to target leverage ratios. Third, increases in lending are associated with security sales. This result makes sense from the perspective that banks are shifting their portfolios towards loans that presumably will generate a larger risk-adjusted profit than its marketable securities. Fourth, drawn commitments or letters of credit are associated with bank selling. Fifth, larger beginning-of-period cash positions are associated with less selling. Sixth, we are able to explain sales in all securities much better than sales of risky securities in particular. Finally, whatever motivates the selling of risky securities, it is persistent across quarters.

In the third step, we use machine learning techniques to assess the extent to which bank security sales can be predicted out-of-sample and which ex ante factors are important in doing so. We find very little explanatory power when we perform an in-sample regression analysis using only variables that are measured on an ex ante basis from the perspective of the bank sale. Therefore we appeal to machine learning techniques to sift through the hundreds of potentially useful bank-level variables available in data from regulatory filings. The use of machine learning in the empirical finance literature has been growing over the past several years. Examples include using machine learning models to predict default in the credit market (Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2020), select directors (Erel, Stern, Tan, and Weisbach, Forthcoming), predict stock returns (Chinco, Clark-Joseph, and Ye, 2019; DeMiguel, Martin-Utrera, Nogales, and Uppal, 2020; Gu, Kelly, and Xiu, 2020; Moritz and Zimmermann, 2016; Rossi, 2018), and predict bond returns (Bali, Goyal, Huang, Jiang, and Wen, 2021; Bianchi, Büchner, and Tamoni, Forthcoming).

Our analysis focuses on two machine learning models: elastic net and gradient boosted regression trees. By including the broader set of BHC characteristics and using machine learning models, the out-of-sample R^2s are improved. Similar to our in-sample anlaysis, we also find that it is more difficult to forecast the selling of risky securities than safe securities. Interestingly, fewer BHC characteristics are relevant for predicting risky securities, and accounting for their nonlinear interactions is crucial for improving the forecasts. In sum, machine learning models add to our understanding of bank selling by finding influential predictors that we had not selected in our in-sample analysis. For instance, the weighted average interest return on securities contributes to predicting total securities selling, whereas the share of long-term debt repricing within one year is important for forecasting the selling of risky securities.

The contributions from our paper are twofold. First, we provide a new set of empirical facts regarding the selling of securities by banks. Specifically, we find that contemporaneous changes in short-term liabilities (particularly deposits) are the factors most associated with selling decisions, but initial cash holdings and changes to bank capital or loans are also important. We hope that these insights and estimates can be useful in future research. For example, our results suggest that structural models of fire sales in the banking sector should consider both funding and asset shocks as drivers of selling decisions.

Second, our model estimates could be used as an input by regulators in monitoring and supervising the banking sector. From a monitoring perspective, one could construct forecasts of securities selling activity conditional upon current bank balance sheets and a set of hypothetical shocks. This type of measure would complement existing measures of indirect contagion risk such as those of Duarte and Eisenbach (2018). Our model estimates could also be applied in supervisory activities such as annual stress testing exercises. In this setting, regulators could incorporate expected selling activity associated with any given stress scenario.

2 Measuring Security Sales by Banks

To measure historical bank selling activity, we use bank holding company (BHC) data collected by the Federal Reserve through the *Consolidated Financial Statements for Holding Companies* filing, commonly abbreviated as the FR Y-9C. The FR Y-9C elicits relatively detailed balance sheet and income statement information from BHCs on a quarterly basis. Of particular use for this study, it provides a detailed breakdown of securities portfolios held in their banking book (Schedule HC-B) and trading book (Schedule HC-D).

For the banking book, the FR Y-9C further requires BHCs to provide both assessments of "Amortized Cost" (AC) and "Fair value" (FV) for each line item of securities. Although the definitions are not exactly the same, one can roughly think of AC as book value and FV as an estimate of market value. This distinction is required because securities classified as held-to-maturity (HTM) are recorded at their AC on the BHC's consolidated balance sheet while securities classified as available-for-sale are recorded at their FV.

The fact that BHCs report both sets of values (AC and FV) for each security line item in their banking book allows us to calculate separately the net amount of securities sold in a given quarter and the percent change in the market value of the starting/ending bundles. To understand how, consider the transition equations for AC and FV amounts. For a security type i, the transition equations for the AC and FV of a bank j's holdings in their banking book from period $t-1$ to t are

$$AC^{bb}_{j,i,t} = (1 - s^{bb}_{j,i,t})AC^{bb}_{j,i,t-1} \tag{1}$$

$$FV^{bb}_{j,i,t} = (1 - s^{bb}_{j,i,t})(1 - \Psi^{bb}_{j,i,t})FV^{bb}_{j,i,t-1} \tag{2}$$

where $s^{bb}_{j,i,t}$ is the net share of the banking book holdings sold during the quarter and $\Psi^{bb}_{j,i,t}$ is net percent decline in the market value of the holdings over the quarter. We are careful to use the term “net" because we do not and cannot observe gross purchases or sales during the period in the FR Y-9C data.

Rearranging (1) and (2), the expression for the net share sold of security type i by bank j in their banking book between $t-1$ and t is

$$s^{bb}_{j,i,t} = \frac{AC^{bb}_{j,i,t-1} - AC^{bb}_{j,i,t}}{AC^{bb}_{j,i,t-1}} \tag{3}$$

and the expression for net percent decline in market value is

$$\Psi^{bb}_{j,i,t} = 1 - \frac{FV^{bb}_{j,i,t}}{(1 - s^{bb}_{j,i,t})FV^{bb}_{j,i,t-1}} \tag{4}$$

A limitation of the FR Y-9C data from our perspective is that AC values are only reported separately for securities held on the banking book, not securities held in the trading book. Only FV values are reported for securities held on the trading book. We estimate the net share of the holdings in the trading book sold of security type i by bank j using the following expression

$$s^{tb}_{j,i,t} = 1 - \frac{FV^{tb}_{j,i,t}}{FV^{tb}_{j,i,t-1}(1 - \Psi^{bb}_{agg,i,t})} \tag{5}$$

where $\Psi^{bb}_{agg,i,t}$ is the net market price decline computed according to (4) using the banking book holdings (AC and FV) of security type i aggregated across all BHCs. We use aggregated data instead of the individual bank's data to avoid the potentially distortive impact of outlier values on the net share sold estimates.

The computed net sold and net market value decline figures described above can be converted from decimals to dollar amounts as follows. First, we can compute the dollar amounts sold estimates by multiplying them by the beginning of period balances as follows

$$sold^{bb}_{j,i,t} = s^{bb}_{j,i,t} AC^{bb}_{j,i,t-1} \tag{6}$$

$$sold^{tb}_{j,i,t} = s^{tb}_{j,i,t} FV^{tb}_{j,i,t-1} \tag{7}$$

Next, we can compute unrealized losses (i.e., the dollar amounts of the market value declines after accounting for net amounts sold) as follows

$$unreal^{bb}_{j,i,t} = \left(\frac{\Psi^{bb}_{j,i,t}}{1 - \Psi^{bb}_{j,i,t}} \right) FV^{bb}_{j,i,t} \tag{8}$$

$$unreal^{tb}_{j,i,t} = \left(\frac{\Psi^{bb}_{agg,i,t}}{1 - \Psi^{bb}_{agg,i,t}} \right) FV^{tb}_{j,i,t} \tag{9}$$

Further, these subtotals from the banking and trading books can be summed together to compute overall estimates for bank j's holdings of security type i

$$sold_{j,i,t} = sold^{bb}_{j,i,t} + sold^{tb}_{j,i,t} \tag{10}$$

$$unreal_{j,i,t} = unreal^{bb}_{j,i,t} + unreal^{tb}_{j,i,t} \tag{11}$$

Finally, these amounts can be summed across all security types for bank j to compute

$$sold_{j,tot,t} = \sum_i sold_{j,i,t} \tag{12}$$

$$unreal_{j,tot,t} = \sum_i unreal_{j,i,t} \tag{13}$$

The above formulas can also be applied to any specific set of security types.

3 Stylized Facts about Bank Security Sales

In this section, we describe the empirical measures of bank selling from section 2. We aim to provide stylized facts about bank selling activity both across banks and across time. Our analysis focuses on larger BHCs in order to present an accurate and consistent description of BHC selling over time. Specifically, we exclude BHC subsidiaries whose assets are already captured in their parent's filings, nontraditional BHCs, and small BHCs that do not consistently report their data on a quarterly basis or with sufficient detail. See Appendix A for more details about our sample construction. Nonetheless, the BHCs in our analysis sample comprise the majority of traditional BHC assets. Importantly, they also hold almost all of the risky securities held within the traditional BHC sector.

Before delving into specific selling measures, however, it is helpful to first review the overall asset portfolio of BHCs. The reason to do so is to provide some context for the amount and types of securities that BHCs can sell during distress. In the top left panel of Figure 1, we report that aggregate BHC assets have increased from \$5 trillion to \$20 trillion between 2000 and 2020. During the same time, the number of BHCs have steadily declined from roughly 750 to 250 (top right panel). Remember these are the BHC counts in our analysis sample, which excludes nontraditional BHCs and smaller BHCs that do not consistently file a FR Y-9C throughout the sample period. In the bottom left panel, we report that roughly 25% of BHC assets are marketable securities, which we define as all non-derivative security types reported in a bank's banking book (Schedule HC-B) or trading book (Schedule HC-D). For reference, the equivalent figure for BHC loan assets is roughly 55% on average. In terms of the composition of BHC securities, the percent that we define as risky (e.g., private-label mortgage-backed securities or asset-backed securities) has varied substantially over our sample period. This share peaked at 60% at the end of 2007 and has declined steadily since then. Looking in the cross section, we note that most BHCs hold much smaller shares of risky securities (i.e., the median share has consistently been around 25%) even though they hold similar amounts of securities relative to total assets. This implies that the decline in the aggregate share has been driven by large BHCs.

BHCs as a whole tend to be net purchasers of securities, although we do observe individual quarters with large selling volume. In Figure 2, we report aggregated measures of BHC selling activity over time. In the left panel, we show the sum of the net amounts sold but only for BHCs that net sold a positive amount. As such, this series proxies for the gross amount sold by the BHC sector as a whole. We observe that these selling flows do vary over time and tend to be well under \$100 billion dollars in any given quarter. The first and fourth quarters of 2008 are outliers from this perspective with selling volumes over \$200 billion. The fourth quarter observation in particular make sense given that this was the

Figure 1. Bank Holding Companies in Aggregate

The solid line in the cross section panels is the median and the dashed lines are the 25th and 75th percentile values. Data are from the Federal Reserve FR Y-9C. Sample only includes traditional BHCs that consistently file form FR Y-9C throughout the analysis period. See Appendix A for sample construction details and variable definitions.

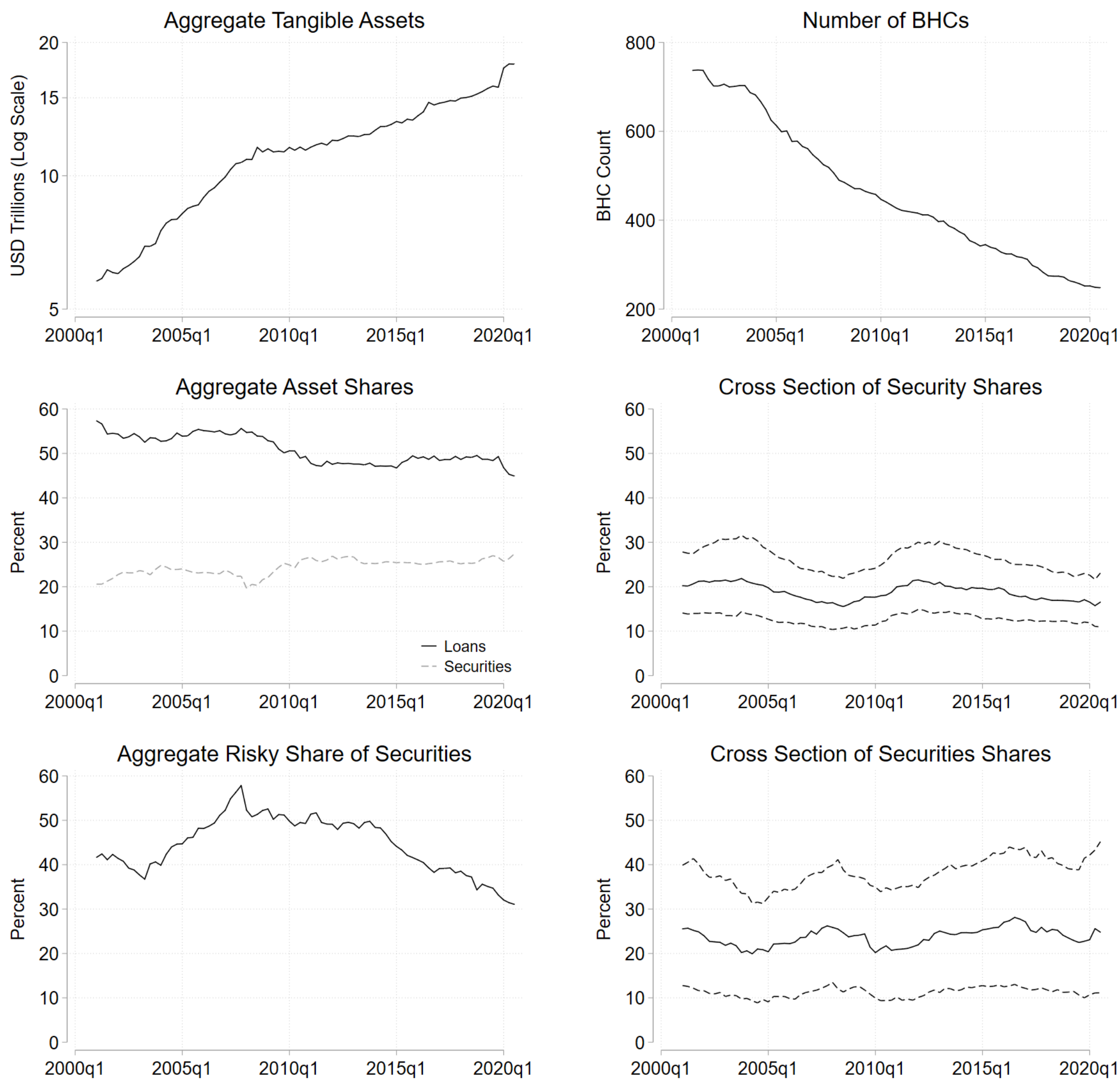
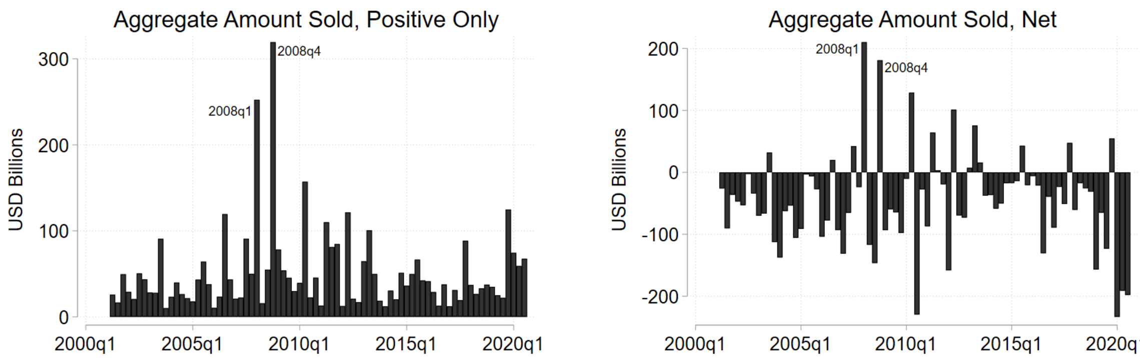


Figure 2. Bank Holding Company Securities Selling in Aggregate
Amounts sold for each BHC are computed as described in section 2. Underlying data are from the Federal Reserve FR Y-9C. Sample only includes traditional BHCs that consistently file form FR Y-9C throughout the analysis period. See Appendix A for sample construction details and variable definitions.

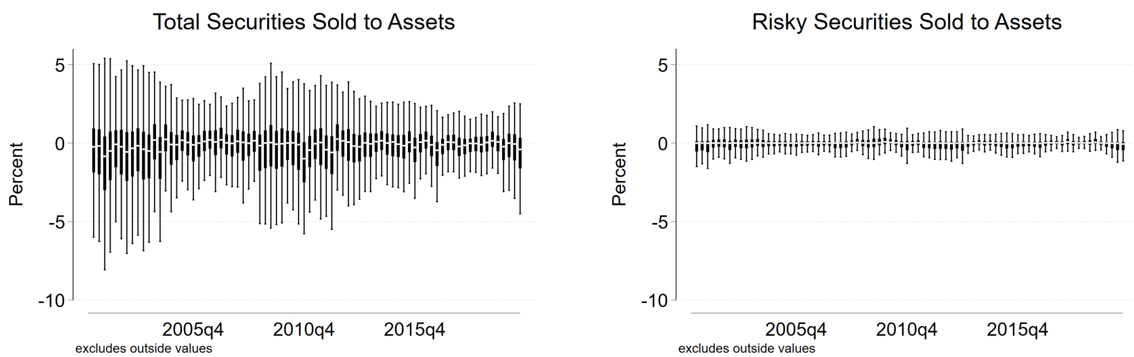


quarter in which the financial system was under significant distress and there was significant anecdotal evidence of fire sale activity. In the right panel, we report the sum of all net selling flows, which include also the flows from BHCs that were net purchasers of securities in each period. Here, we see that 2008 is still an outlier in terms of large selling volume. We also see that, in most quarters, the BHC sector as a whole is actually a net purchaser of securities.

We are also interested in understanding the composition of BHC selling activity. In particular, we can decompose observed sales into the shares coming from safe securities versus risky securities. We define safe securities as U.S. Treasury securities, U.S. government agency obligations, and agency mortgage-backed securities (MBS). We define risky securities as everything else, which include non-agency MBS, asset-backed securities (ABS), corporate debt, structured financial products (SFP), equities, and municipal bonds. The common themes of the risky securities are the existence of nontrivial credit risk and the notion that these types of securities can experience price declines during periods of large selling volumes.

BHCs tend to use safe securities (e.g., U.S. treasuries) when adjusting their portfolio. In Figure 3, we report cross-sectional measures of BHC selling over time. In the left panel, we observe that the average volume of selling is close to zero throughout the sample with most selling decisions being plus or minus a couple of percentage points in terms of amount sold to assets. In the right panel, we see that amounts sold of risky securities (e.g., asset-backed securities) tend to be much smaller in comparison. As such, we can infer that BHCs

Figure 3. Securities Selling Across Bank Holding Companies
Amounts sold for each BHC are computed as described in section 2. Underlying data are from the Federal Reserve FR Y-9C. Sample only includes traditional BHCs that consistently file form FR Y-9C throughout the analysis period. See Appendix A for sample construction details and variable definitions.



tend to use their safe securities when making selling decisions. This outcome is perhaps not surprising considering that only 20% of the median BHC's security holdings are risky (Figure 1).

We can further confirm the tendency for BHCs to exclusively sell safe securities when engaging in a large security sales by examining the composition of individual sales. In figure 4, we report separately the amounts of risky versus safe securities sold in observed BHC sales (i.e., cases where total securities sold were positive). The greater density of points for which risky securities sold are close to zero while safe securities sold are positive reveals that the most common type of sale is one in which a bank sells only safe securities. Of course other permutations of bank selling occurred too. For example, we can see that there were cases in which a bank only sells risky securities, and there are also cases in which a bank sells both safe and risky securities at the same time.

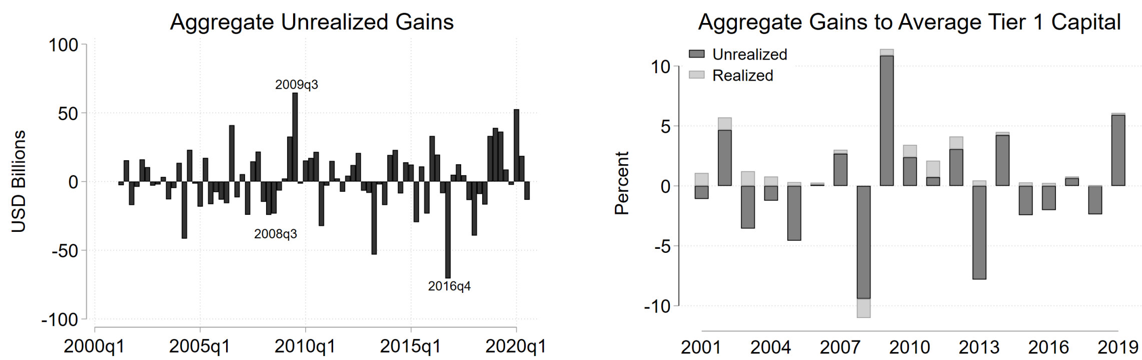
Selling activity can create losses for banks in two different ways. The first way is that a bank that sells a security after its price has gone down suffers a realized loss. This type of loss is captured directly in a line item in a bank's income statement as reported on the FR Y-9C. Selling activity can also create unrealized losses for a bank if the market value of its security holdings decline as a result. This type of loss can be generated by a bank's own selling activity or the selling activity of other investors. Despite the fact that unrealized losses do not generally affect a bank's regulatory capital calculations (Beatty and Liao, 2014),

Figure 4. Composition of Bank Holding Company Sales
Each dot represents a quarterly observation in which a BHC sold a positive amount of securities in total. For visual purposes, we exclude extreme cases in which a BHC's amount sold was more than 10% of its assets. Amounts sold for each BHC are computed as described in section 2. Underlying data are from the Federal Reserve FR Y-9C. Sample only includes traditional BHCs that consistently file form FR Y-9C throughout the analysis period. See Appendix A for sample construction details and variable definitions.

many have argued that mark-to-market accounting combined with this type of indirect loss can both cause and exacerbate fire sales (see, e.g., Ellul, Jotikasthira, Lundblad, and Wang, 2014; Plantin, Sapra, and Shin, 2008).

Unrealized losses can be quite sizable for banks, both in aggregate and relative to realized losses. In the left panel of figure 5, we report unrealized gains over time. There are a few interesting periods worth pointing out. First of all, unrealized losses were consistent throughout 2008, peaking in the third quarter. In 2009, these unrealized losses appeared to reverse as the third quarter of 2009 saw the largest amount of unrealized gains over the sample. In the fourth quarter of 2016, we observed the largest aggregate unrealized losses of the sample. This quarter coincides with the unexpected election of President Trump and the subsequent rise in interest rates. As such, there were large declines in the market values of safe securities. As a general takeaway, aggregate unrealized gains fluctuate over time and appear to be driven in large part by shifts in the macro-financial environment. In the right panel of figure 5, we put both unrealized gains and realized gains into perspective by dividing

Figure 5. Aggregate Losses Related to Security Holdings and Sales
Underlying losses for each BHC-quarter are computed as described in section 2. Underlying data are from the Federal Reserve FR Y-9C. Sample only includes traditional BHCs that consistently file form FR Y-9C throughout the analysis period. See Appendix A for sample construction details and variable definitions.



them by tier 1 capital. Here, we observe that the unrealized losses in 2008 were substantial at roughly 10% of tier 1 capital. These losses appeared to reverse entirely in 2009. Realized gains/losses, on the other hand, tend to be much smaller in any given period.

In summary, we observe in the data that the banking sector as a whole tends to be a net purchaser of securities, with a few key exceptions (e.g., during financial distress in 2008). Banks tends to sell safe securities when they do, but there are numerous cases in which they choose to primarily sell risky securities instead. Finally, unrealized losses as measured directly from securities holdings can be quite large.

4 Factors Associated with Bank Security Sales

In this section, we move beyond the descriptive analysis of section 3 to a regression analysis at the BHC-quarter level. The goal is to establish the factors associated with observed bank selling activity. We are careful to use the word "associated" because, without appealing to a structural model or relying on a credible identification strategy, we cannot rule out reverse causality or unobserved confounding factors to explain our findings. Nonetheless, our analysis in this section serve to deepen our understanding of bank selling activity by identifying key empirical relationships and corresponding magnitudes.

4.1 Contemporaneous Factors and Ex Ante Factors

In our first set of tests, we consider both contemporaneous and ex ante explanatory variables. For our empirical specification, we regress a measure of securities sold on a set of bank-quarter-level variables as well as fixed effects. Specifically, we run regressions of the following form:

$$(\text{Securities Sold / Assets})_{i,t} = \beta' X_{i,t} + \eta_i + \eta_t + \epsilon_{i,t} \tag{14}$$

where the dependent variable is the ratio of the amount of securities sold to the beginning of period tangible assets. We consider this measure using both total securities ("All Securities") and risky securities only ("Risky Only"). The bank-quarter-level variables (X) are either contemporaneous or ex ante from the perspective of the given period's sale. The terms η_i and η_t represent bank and time fixed effects.

Our contemporaneous bank-quarter variables are meant to capture the conditions of the bank during the period in which it sold securities. Changes in short-term liabilities such as deposits or repurchase agreements ("repo") can proxy for sudden withdrawals by short-term creditors that are often cited in historical accounts of financial fire sales (e.g., Shleifer and Vishny, 2011). Similarly, changes in the cost of funds (specifically a sudden increase) would likely be associated with these types of episodes. We consider changes in tier 1 capital, changes in market capitalization, net charge-off rates, the return from unrealized gains, and return on assets as proxies for shocks to the value of a bank's assets. Many structural models of indirect contagion (e.g., Greenwood et al., 2015) consider these shocks to be of first-order importance in causing leverage to deviate from target, which then leads to asset selling. We also consider measures of a bank's need to fund new loans investments, which could coincide with a bank choosing to sell securities. These measures include the change in total loans, the change in unused off-balance sheet commitments, and the change in the off-balance-sheet amount of financial standby letters of credit. For the off-balance-sheet measures, a decrease may indicate the materialization of the underlying commitment.

Our ex ante bank-quarter variables capture the condition of the bank entering a given quarter. These include it's regulatory capital position and its relative share of security holdings, trading assets, and cash. We might expect a bank with a lower capital ratio would be more likely to engage in asset sales to avoid falling below its required level (Coen et al., 2019; Kirti and Narasiman, 2017). We might also expect a bank with more cash holdings would be less likely to sell securities because it could use cash to meet unexpected obligations instead. Finally, we include the previous period's selling outcomes in case selling decisions are persistent over time.

There are several key takeaways from our regression results, which we present in Table 1. First off, we find that the measures of changes in short-term liabilities contribute to the majority of our explanatory power. Moreover, the signs of the coefficients are negative, which aligns with the theory of creditor-induced fire sales, and have a simple interpretation. For example, a coefficient of -0.534 for the change in repo implies that for each dollar decline in repo funding, the bank sells 53.4 cents of securities.[1]

Second, we find strong evidence for the explanatory power for declines in tier 1 capital being associated with security sales. Tier 1 capital can decline from either income losses and declines in asset values. As a a result, a bank's capital ratio will be lower before any adjustments to its risk-weighted asset base. Thus this finding supports both the view that regulatory capital constraints can incentivize asset sales and the view that banks will sell to return to target leverage ratios. The latter point can be made given that the same tier 1 capital numerator goes into a bank's capital and leverage ratios.

Third, increases in lending are associated with security sales. Specifically, our coefficient estimates suggest that for each additional dollar in loans, a bank sells roughly 20 cents of securities and 2 cents of risky securities, all else equal. Given that we also control for changes in unused commitments and financial standby letters of credit, this interpretation seems to apply to new loans that are not driven by drawn commitments. This result makes sense from the perspective that banks are shifting their portfolios towards loans that presumably will generate a larger risk-adjusted profit than its marketable securities.

Fourth, drawn commitments or letters of credit are associated with bank selling. We proxy for the amount drawn simply by the change in the stock of these commitments. The coefficient on the change in financial standby letters of credit is particularly large, suggesting that a bank sells between 25-35 cents of securities and 13-14 cents of risky securities for each dollar reduction in financial standby letters of credit, all else equal. The magnitudes for

[1]In this case, both the left- and right-hand side variable are divided by beginning of period assets. Many of our explanatory variables are similarly divided by beginning of period assets, which will allow for similar interpretations of their coefficients.

Table 1. Explaining Securities Sold to Assets Ratios Using Contemporaneous Variables

This table shows the coefficient estimates from the following regression:

$$(\text{Securities Sold / Assets})_{i,t} = \beta' X_{i,t} + \eta_i + \eta_t + \epsilon_{i,t}$$

where the dependent variable is the ratio of the amount of securities sold to the beginning of period tangible assets. We consider this measure using both total securities ("All Securities") and risky securities only ("Risky Only"). See section 2 for a description of how we measure the amounts of securities sold and see Appendix A for details regarding variable construction and data sources. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	All Securities	Risky Only	All Securities	Risky Only	All Securities	Risky Only
Δ Deposits / Assets	-0.174***	-0.035***	-0.265***	-0.039***	-0.267***	-0.040***
	(-32.24)	(-15.98)	(-37.24)	(-13.85)	(-36.37)	(-13.31)
Δ Repo / Assets	-0.534***	-0.069***	-0.589***	-0.067***	-0.580***	-0.066***
	(-19.16)	(-6.40)	(-22.27)	(-6.28)	(-22.31)	(-6.18)
Δ FFP / Assets	-0.353***	-0.083***	-0.450***	-0.090***	-0.441***	-0.088***
	(-16.06)	(-9.27)	(-21.33)	(-9.79)	(-21.02)	(-9.48)
Δ Cost of Funds			1.857***	0.113	-1.299	-0.273
			(4.46)	(0.60)	(-1.55)	(-0.71)
Starting Tier 1 Capital Ratio			-0.010	-0.006*	-0.028***	-0.006
			(-1.15)	(-1.72)	(-2.81)	(-1.44)
Δ Tier 1 / Assets			-0.500***	-0.116***	-0.482***	-0.117***
			(-12.07)	(-6.87)	(-11.52)	(-6.74)
Δ Mkt. Cap. / Assets			-0.015*	0.002	-0.011	-0.007
			(-1.89)	(0.54)	(-1.12)	(-1.53)
Net Charge-off Rate			-0.123	-0.044	0.072	-0.052
			(-1.07)	(-0.89)	(0.57)	(-0.97)
Unrealized Gain Return			0.344***	0.016	0.441***	0.063***
			(11.37)	(1.30)	(8.20)	(2.74)
ROA			-0.043	-0.036***	-0.026	-0.032***
			(-1.54)	(-3.12)	(-0.89)	(-2.61)
Δ Loan / Assets			0.194***	0.019***	0.194***	0.020***
			(21.85)	(5.00)	(21.42)	(5.19)
Δ Unuse. Comm. / Assets			-0.019**	-0.008**	-0.026***	-0.009**
			(-2.13)	(-1.97)	(-2.90)	(-2.15)
Δ Fin. Standby LOC / Assets			-0.348***	-0.136**	-0.253**	-0.127**
			(-3.01)	(-2.51)	(-2.17)	(-2.33)
Starting Securities / Assets			0.009***	-0.005***	0.013***	-0.005***
			(2.66)	(-3.14)	(3.49)	(-3.10)
Starting Trading Securities / Assets			0.034	0.030	0.045	0.033*
			(0.73)	(1.52)	(0.99)	(1.72)
Starting Cash+FFS+Rev. Repo / Assets			-0.158***	-0.012***	-0.155***	-0.010***
			(-22.57)	(-4.64)	(-21.57)	(-3.81)
Last Period Securities Sold / Assets			0.013	-0.007*	0.006	-0.006
			(1.15)	(-1.67)	(0.56)	(-1.31)
Last Period Risky Securities Sold / Assets			0.029	0.080***	0.048*	0.073***
			(1.07)	(4.96)	(1.75)	(4.48)
Agg. Price Decline in Risky Securities			-0.039***	-0.010*		
			(-2.97)	(-1.83)		
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes
R^2	0.197	0.089	0.299	0.108	0.317	0.121
N	16216	16216	16155	16155	16155	16155

drawn lending commitments are significantly smaller (2–3 cents and 1 cent, respectively). This difference may reflect the fact that selling induced from drawn loan commitments is already captured in part in the change in lending coefficient.

Fifth, we find that larger beginning-of-period cash positions are associated with less selling. Here we measure "cash" as the sum of cash, balances due from depository institutions, federal funds sold ("FFS"), and securities purchased under agreements to resell ("reverse repo"). Specifically, we find that each additional dollar in cash is associated with 16 cents less in all securities sold and 1 cent less in risky securities sold.

Sixth, risky securities selling decisions are persistent. The coefficient on last period's risky securities sold is positive and significant, but only for the current risky securities sold. This finding suggests that, whatever motivates the selling of risky securities, it is persistent across quarters. This finding may also be driven by the secular reduction in risky securities holdings from 2010 onward, which was motivated by the tightening of bank regulation following the 2008 Financial Crisis.

Seventh, we observe that the interpretation and impact for a few explanatory variables depend on the inclusion of time fixed effects. The coefficient on the change in cost of funds is only significant without time fixed effects. The fact that it loses its significance means that on its own it is capturing characteristics of the time period rather than a bank-specific factor. The coefficient for beginning-of-period capital ratio is only significant after adding time fixed effects. This finding suggests that it is the relative capital ratio of a bank in a given period that affects a bank selling decisions.

Finally, we find that we are able to explain sales in all securities much better than sales of risky securities in particular. One way to capture this difference is to note that the R^2 is roughly 30% in our full specification with all variables and fixed effects when the dependent variable is measured with all securities, but this number is about 10% when we focus on risky securities. We also note that the magnitudes of all coefficients are smaller when focusing on risky securities sold. Some of this difference can be explained by the fact that most banks only hold between 10% and 40% of their securities portfolio in risky securities (Figure 1). Given the difference in R^2, however, it also seems to be the case that the risky security selling outcomes cannot be explained as well by the variables we are considering.

Next, we provide an initial assessment of the stability of the coefficient estimates from

Figure 6. Stability of Coefficient Estimates Over Time for All Securities

The panels below show the coefficient estimates and corresponding 90% confidence intervals for select variables from the regression specification in Table 1 for All Securities except that the regressions are run without bank fixed effects and performed separately in each quarter. The red dashed lines indicate the coefficient estimate from the regression run on the full sample, which may differ slightly from the figure presented in Table 1 because we omit bank fixed effects in this analysis. See section 2 for a description of how we measure the amounts of securities sold and see Appendix A for details regarding variable construction and data sources. Standard errors used to construct confidence intervals are heteroskedasticity-consistent.

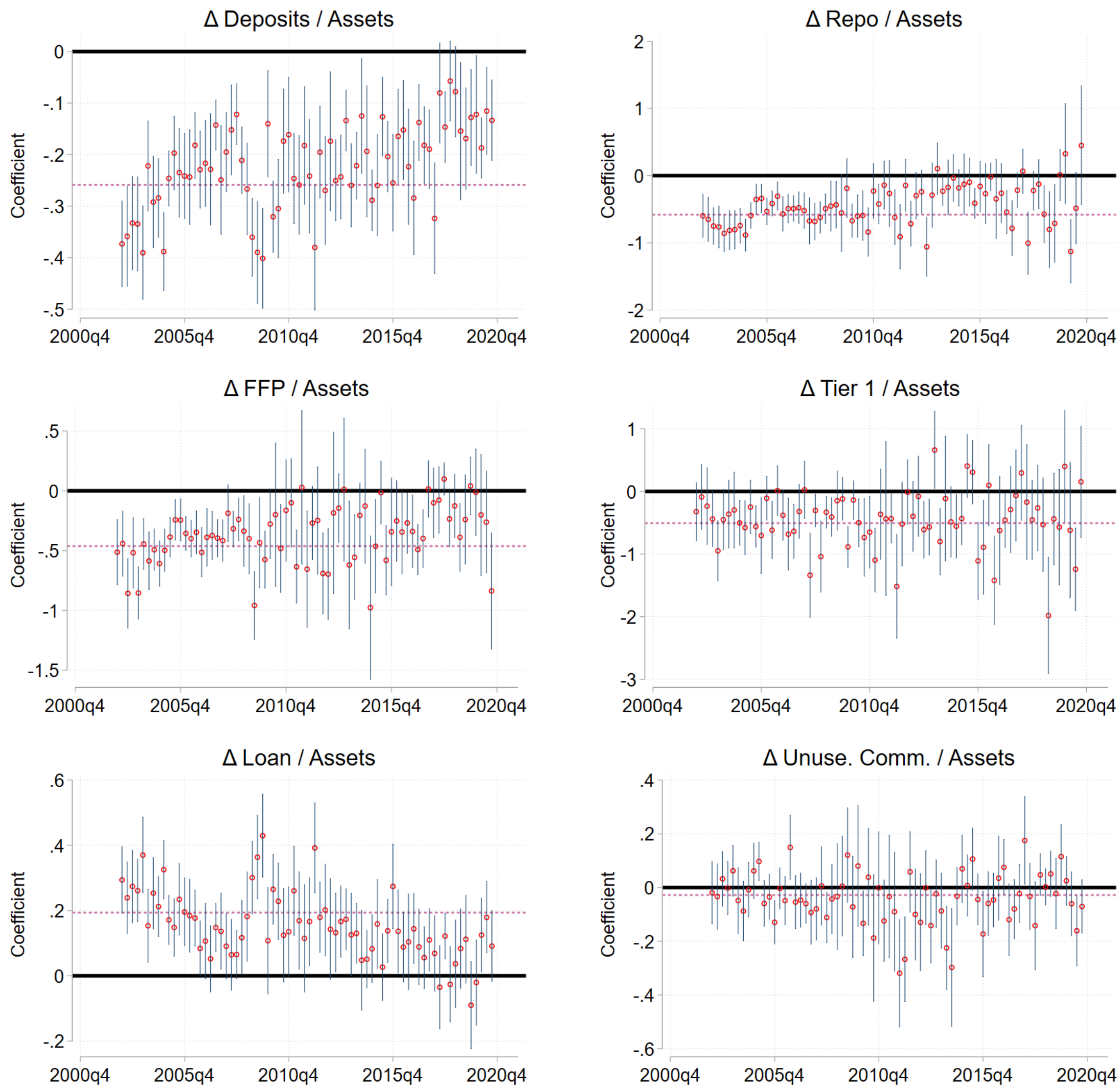


Table 1 over time. Specifically, we compute the coefficient estimates and confidence intervals from cross-sectional regressions (i.e., separate regressions performed for each quarter). We plot these values in Figure 6 for the key variables discussed above. The main takeaway from this figure is that the coefficient values for these variables appear to have at least some time variation in their magnitude. For some variables, the coefficient estimates display spikes in certain time periods while for others the magnitude shifts over the sample. Without further analysis involving a clear identification strategy, we cannot make any conclusions beyond simply noting these general points. Possible reasons for changing relationships between bank-level outcomes and selling decisions are that financial market conditions matter and that new regulations enacted throughout the sample affected the bank decision making process. Additionally, central bank facilities created to purchase financial assets would likely have such effects. On this note, a few of the spikes in coefficient values (e.g., for changes in deposits and loans) occur in 2009, which is the period in which the Federal Reserve began operation of the Term Asset-Backed Securities Loan Facility (TALF) among many other actions. We plan to investigate these specific channels as we develop our analysis further.

As another follow-up to our analysis presented in Table 1, we consider whether observed selling has asymmetric relationships with the key contemporaneous variables described above. We do so by running the same regression as in (14) except that we modify the set of explanatory variables. Specifically, we replace several key variables with positive- and negative-only versions of themselves. For example, the positive-only component of $\Delta Deposits/Assets$ is a variable that is equal to the underlying variable when it is positive and zero otherwise. By including both the positive-only and negative-only components as separate variables in the same regression, we can identify asymmetry if the coefficient estimates are different both statistically and economically.

In Table 2, we present evidence supporting an asymmetric relationship with securities selling for some but not all important contemporaneous variables. First off, we find similar coefficient estimates for the change in deposits. However, the magnitudes of the coefficients are larger for positive changes in repo and FFP. This finding means that banks tend to buy more securities in quarters in which repo and FFP increase compared to the amounts they sell in quarters in which these liabilities decline. Second, banks appear to only sell more securities in quarters in which their cost of funds increases but decreases are not associated

Table 2. Assessing Asymmetry Between Selling and Contemporaneous Variables

This table shows the coefficient estimates from the following regression:

$$(\text{Securities Sold / Assets})_{i,t} = \beta' X_{i,t} + \eta_t + \epsilon_{i,t}$$

where the dependent variable is the ratio of the amount of securities sold to the beginning of period tangible assets. We consider this measure using both total securities ("All Securities") and risky securities only ("Risky Only"). The "Positive" and "Negative" columns display the coefficient estimates corresponding to the positive-only and negative-only components of the same variables, respectively, that are both included within the same regression model. For example, the positive-only component of $\Delta Deposits/Assets$ is a variable that is equal to the underlying variable when it is positive and zero otherwise. "Other Bank Controls" refers to the other variables presented in Table 1 that are not presented in this table because we do not separate them into their positive and negative components. See section 2 for a description of how we measure the amounts of securities sold and see Appendix A for details regarding variable construction and data sources. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	All Securities		Risky Only	
	Positive	Negative	Positive	Negative
Δ Deposits / Assets	-0.265***	-0.235***	-0.039***	-0.032***
	(-28.18)	(-14.17)	(-10.61)	(-4.64)
Δ Repo / Assets	-0.660***	-0.486***	-0.070***	-0.061***
	(-15.21)	(-11.29)	(-3.90)	(-3.52)
Δ FFP / Assets	-0.494***	-0.387***	-0.104***	-0.072***
	(-13.99)	(-11.12)	(-6.47)	(-5.15)
Δ Cost of Funds	3.742***	0.044	0.395	-0.116
	(4.74)	(0.06)	(1.08)	(-0.38)
Δ Tier 1 / Assets	-0.534***	-0.229**	-0.123***	-0.065
	(-10.33)	(-2.50)	(-5.93)	(-1.58)
Δ Mkt. Cap. / Assets	-0.047***	0.031**	-0.003	0.010
	(-3.63)	(2.10)	(-0.54)	(1.59)
Unrealized Gain Return	-0.061	0.681***	0.036	-0.001
	(-1.04)	(12.85)	(1.46)	(-0.03)
Δ Loan / Assets	0.192***	0.279***	0.020***	0.033***
	(17.11)	(10.43)	(4.28)	(2.90)
Δ Unuse. Comm. / Assets	-0.021	-0.005	-0.020***	0.015**
	(-1.52)	(-0.28)	(-3.20)	(2.05)
Δ Fin. Standby LOC / Assets	-0.421**	-0.115	-0.142*	-0.104
	(-2.41)	(-0.54)	(-1.72)	(-1.11)
Agg. Price Decline in Risky Securities	-0.002	-0.040*	-0.001	-0.018**
	(-0.08)	(-1.79)	(-0.15)	(-2.00)
Other Bank Controls	Yes		Yes	
Bank FE	Yes		Yes	
Time FE	No		No	
R^2	0.307		0.110	
N	16155		16155	

with selling at all. This finding is line with the notion that security sales are driven by deleveraging associated with sudden increases in the cost of funds, an outcome which itself could be driven by a multitude of firm-specific factors or market-wide distress.

The coefficient on the negative-only component of change in loans is larger than than positive-only component for sales of all securities, suggesting that banks sell less during quarters in which their loans increase compared to purchases when loans decline. Combined with the fact that the coefficients on change in unused commitments are not significant, this result supports the view that selling activity associated with changes in loan balance represents the bank shifting their portfolio from loans to securities. Similarly, it may represent a bank investing a portion of the proceeds from repaid loans in securities rather making new loans. In other words, these sales do not seem as strongly driven by the need to fund new loans.

Our interpretation of a similar finding in the case of risky securities is different from the all securities case because the coefficients on the change in unused commitments are now significant. For positive changes in loans being associated with risky securities sales, the specific coefficient values suggest that this entire effect is related to drawn commitments. In other words, the identical coefficient estimates suggest that banks sell risky securities to fund a small portion of drawn commitments. The sign on the negative-only component is actually positive for risky securities, which implies that banks actually buy risky securities when commitments are drawn.

4.2 Ex Ante Factors Only

In our second set of tests, we restrict our attention to only ex ante variables from the perspective of the observed bank selling sale. Specifically, we run regressions of the following form:

$$\text{(Securities Sold / Assets)}_{i,t} = \beta' X_{i,t} + \eta_i + \epsilon_{i,t} \tag{15}$$

This specification is similar to (14) except that exclude time fixed effects and also the set of bank-level variables are restricted to be ex ante.

Given our focus on ex ante factors, we use a slightly modified set of explanatory variables. For example, we include the beginning-of-period value of the share of assets financed by repo instead of the change in repo. We also include the average risk weight of the banks

Table 3. Explaining Securities Sold to Assets Ratios Using Only Ex Ante Variables
This table shows the coefficient estimates from the following regression:

$$\left(\text{Securities Sold / Assets}\right)_{i,t} = \beta' X_{i,t} + \eta_i + \epsilon_{i,t}$$

where the dependent variable is the ratio of the amount of securities sold to the beginning of period tangible assets. We consider this measure using both total securities ("All Securities") and risky securities only ("Risky Only"). See section 2 for a description of how we measure the amounts of securities sold and see Appendix A for details regarding variable construction and data sources. Standard errors are heteroskedasticity-consistent. t-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	All Securities	Risky Only	All Securities	Risky Only	All Securities	Risky Only
Starting Tier 1 Leverage Ratio	0.026***	0.008*	0.011	0.000	0.002	-0.003
	(2.66)	(1.91)	(1.09)	(0.04)	(0.12)	(-0.55)
Starting Market Cap. Leverage Ratio	-0.005*	-0.002	-0.001	0.000	-0.009**	-0.001
	(-1.70)	(-1.10)	(-0.44)	(0.08)	(-2.11)	(-0.79)
Starting Repo / Assets			0.010	0.004*	0.011	0.004
			(1.48)	(1.75)	(0.99)	(0.85)
Starting RWA / Assets			0.001	-0.000	-0.001	0.003
			(0.37)	(-0.27)	(-0.31)	(1.29)
Starting Market Risk RWA / RWA			0.016	-0.003	0.012	0.034
			(0.33)	(-0.13)	(0.13)	(0.70)
Starting Securities / Assets			-0.004	-0.005***	0.009*	-0.004*
			(-1.38)	(-4.01)	(1.81)	(-1.65)
Starting Trading Securities / Assets			0.019	-0.006	0.037	0.030
			(0.62)	(-0.38)	(0.72)	(1.41)
Starting Cash+FFS+Rev. Repo / Assets			-0.048***	-0.006***	-0.131***	-0.004
			(-10.05)	(-3.25)	(-14.74)	(-1.30)
Last Period Securities Sold / Assets			0.029**	-0.008*	0.005	-0.009**
			(2.28)	(-1.93)	(0.41)	(-2.11)
Last Period Risky Securities Sold / Assets			0.045	0.123***	0.055*	0.086***
			(1.44)	(7.61)	(1.76)	(5.18)
Bank FE	No	No	No	No	Yes	Yes
Time FE	No	No	No	No	No	No
R^2	0.001	0.001	0.014	0.021	0.066	0.059
N	17130	17130	16155	16155	16155	16155

assets and the fraction of risk-weighted assets coming from market risk as provide ex ante measures of asset riskiness.

There are a few key takeaways from our regression results only using ex ante variables, which we present in Table 3. First off, we find that our set of ex ante variables do not forecast bank sales well. Without bank fixed effects, we achieve R^2 values of 1%–2%. After including bank fixed effects, these numbers increase to 6%–7%. This finding implies that the types of shocks proxied for by contemporaneous variables in Table 1 are key drivers of securities selling.

Second, beginning-of-period cash holdings is the most important predictor for total securities sold. This result holds with and without bank fixed effects. It implies that, while shocks that influence selling cannot be anticipated, a bank with more cash is less likely to sell securities, all else equal.

Finally, last period risky securities sold is the most important predictor for risky securities sold. In contrast to total securities sold, cash holdings are relatively unimportant. Similar to our results from Table 1, this finding suggests that, whatever motivates the selling of risky securities, it is persistent across quarters.

5 Out-of-sample Predictability of Bank Security Sales

In this section, we explore the out-of-sample predictability of bank securities sales. Specifically, we use machine learning tools to find the best-performing predictive models and let the data tell which are the most influential predictors. In doing so, we consider a much broader set of variables compared to those used in the in-sample analysis. Specifically, we include hundreds of potentially useful bank-quarter variables constructed from data available in the FR Y-9C filings. The use of machine learning in the empirical finance literature has been growing over the past several years. Examples include using machine learning models to predict default in the credit market (Fuster et al., 2020), select directors (Erel et al., Forthcoming), predict stock returns (Chinco et al., 2019; DeMiguel et al., 2020; Gu et al., 2020; Moritz and Zimmermann, 2016; Rossi, 2018), and predict bond returns (Bali et al., 2021; Bianchi et al., Forthcoming).

5.1 Methodology

In its most general form, we describe the predictive model for the bank selling activities as

$$(\text{Securities Sold / Assets})_{i,t} = g(Z_{i,t-1}) + \epsilon_{i,t}, \tag{16}$$

where the individual BHCs are indexed by $i = 1, ..., N$ and quarters by $t = 1, ..., T$. We let $Z_{i,t-1}$ to denote an P-dimensional vector of BHC characteristics in the previous period, and assume the $g(\cdot)$ is a flexible function of these predictors.

The model description in (16) nests the standard ordinary least-squares regression framework, which assumes a small number predictors have linear relationships with next period's bank selling activities. However, as we jointly study hundreds of BHC characteristics and have little prior knowledge on how they are related to the selling activities of banks, a simple OLS will, on the one hand, overfit the data, leading to an inflated R^2 and misleading economic inferences while, on the other hand, fail to capture the potential complex nonlinear predictor interactions, resulting in inferior predictive performance. We appeal to machine learning techniques to address both of these concerns.

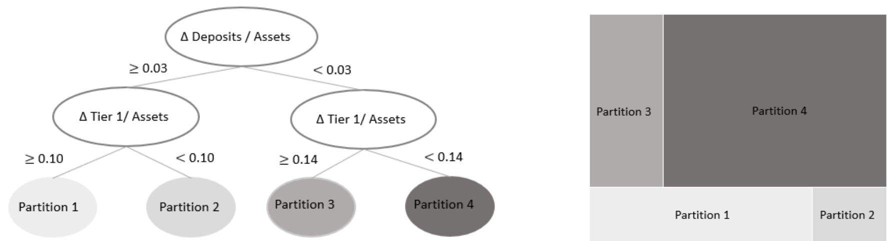
5.1.1 Machine Learning Algorithms. The distinguishing features of machine learning methods are their high-dimensional nature (i.e., allowing for a large number of predictors and a multitude of interaction terms) and the inclusion of regularization. High-dimensional models are highly flexible by construction, enhancing the potential for better capturing unknown and complex relationships. Regularization is the practice of augmenting the model's objective function (e.g., mean squared error) with a penalty on model complexity. It is a defense against the overfitting problem, which refers to the case in which one uses an overly complex model to fit the data in-sample at the expense of out-of-sample performance.

We start with a linear machine learning model, elastic net regression (ENet), for its simplicity. An ENet is prescribed to minimize the standard mean squared error made by the model, augmented with a regularization term that penalizes the total absolute values (L1 penalty) and squares (L2 penalty) of the regression coefficients

$$\mathcal{L}(\beta;\lambda,\alpha) = \underbrace{\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t+1}-\beta_0-\sum_{p=1}^{P}\beta_p z_{i,t}^{p}\right)}_{\text{mean squared error}} + \underbrace{\lambda(1-\alpha)\sum_{p=1}^{P}|\beta_p|}_{\text{L1 penalty}} + \underbrace{\lambda\alpha\sum_{p=1}^{P}\beta_p^2}_{\text{L2 penalty}}, \tag{17}$$

where y represents the Securities Sold / Assets. An ENet involves two regularization parameters, λ and α: λ governs the overall level of penalty. Without any regularization ($\lambda = 0$), ENet collapses to a standard OLS regression. α determines the weights assigned to the $L1$ and $L2$ penalty. Having $\alpha = 0$, ENet becomes a least absolute shrinkage and selection operator (LASSO) regression, which puts the coefficient of less important predictors to zero. Assigning $\alpha = 1$, ENet becomes a ridge regression, which shrinks all the slope coefficients toward zero and each other. For a given pair of (λ, α), the ENet predicts bank security sales

Figure 7. Regression Tree Example
The top panel presents the diagram of a regression tree with four leaves and a depth of three. The equivalent representation for the outcome sample partitions are shown in the bottom panel.



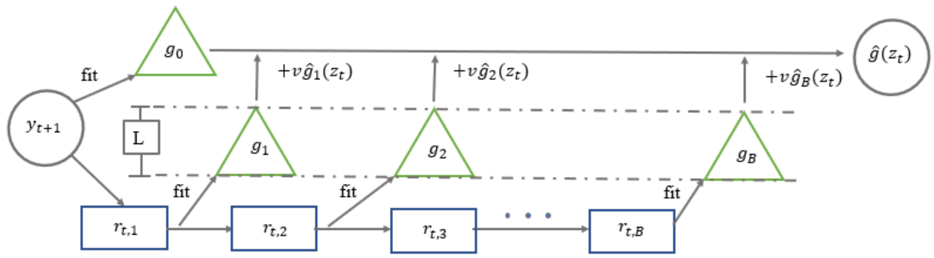
in period t as $\hat{g}(Z_{i,t-1}) = \hat{\beta}_0 + \sum_{p=1}^{P} \hat{\beta}_p z_{i,t-1}^p$.

ENet forms forecasts by linearly combining predictors and is potentially oversimplified if the relation between banks' characteristics and selling activities is actually complex. Thus, we also consider another machine learning model: gradient boosted regression trees (GBRT). Unlike ENet, GBRT accounts for highly flexible nonlinearity and multiway interactions of predictors.

GBRT is a fully non-parametric approach that ensembles predictions from many trees. At a basic level, a tree "grows" in a sequence of steps (illustrated by Figure 7): at each new "branch", the data left over from the preceding step are sorted into bins based on one of the predictors. The average outcome of a terminal partition provides the forecasts for each observation in that partition, $g(Z_{i,t-1}; \theta, K, L) = \sum_{k=1}^{K} \theta_k \mathbf{1}_{Z_{i,t-1} \in C_k(L)}$, assuming the tree has K "leaves" (terminal nodes) and the depth of L (L-1 splits). We use $C_k(L)$ to represents a partition whose average outcome is denoted by θ_k. In each step, the sorting variable and split value are myopically chosen to result in the largest reduction in prediction errors in the current step. Tree-based methods can approximate severe nonlinearities; for instance, a tree with depth L captures $(L-1)$-way interactions.

GBRT combines forecasts from many over-simplified trees. The idea is that though individual shallow trees are "weak learners" with minimum predictive power, combining many of them helps to form a single "strong learner". As illustrated by Figure 8, GBRT recursively fit the residuals (r_{b-1} in blue rectangle) of the ensemble trees from the preceding step ($g_0 + vg_1 + ... + vg_{b-1}$) using a new shallow tree (g_b in green triangle) and augment its fitted value to the prevailing prediction with a shrinkage factor (v), which is the so-called

Figure 8. Gradient Boosted Regression Trees Example
The green triangles represent the shallow trees of depth L, and the blue rectangles represent the residuals from the ensemble trees in each step. v is the learning rate that applies a shrinkage to the prediction from each tree.



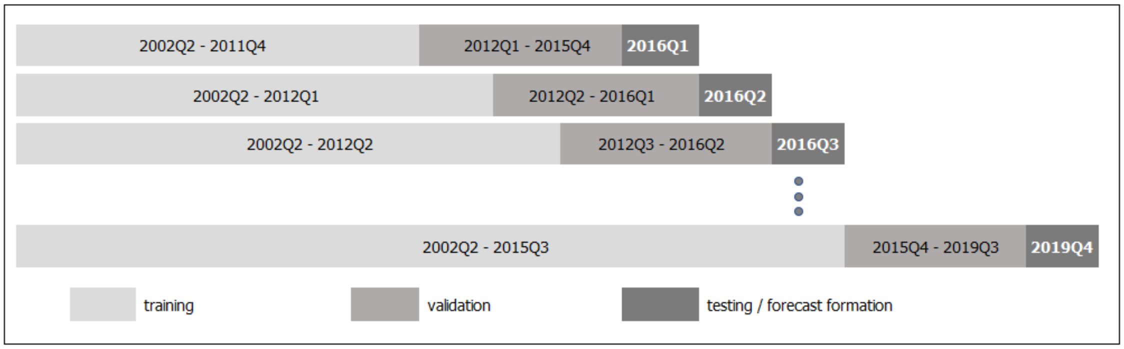
"learning rate" and is prescribed to prevent overfitting. For this approach, the depth of those shallow trees (L), the learning rate (v), and the total number of trees combined (B) are the regularization parameters.

The optimal regularization parameters (λ, α) for ENet, and (L, v, B) for GBRT are chosen adaptively in the data, as described below, to achieve the best out-of-sample predictive performance.

5.1.2 Sample Splitting. The regularization in machine learning prevents overfitting by penalizing the model flexibility. An over-regularized model tends to be overly simplified to approximate complex predictive relationships, whereas an under-regularized model will overfit the data resulting in a poor out-of-sample predictive performance. We choose the optimal regularization parameters, i.e., (λ, α) for ENet and (L, v, B) for GBRT, through cross-validation.

We split the sample into three disjoint training, validation, and testing subsamples respecting their chronological order. Using the training subsample, we estimate the model and obtain the model parameters for given regularization parameters. On the validation subsample, we construct forecasts as the fitted value of the model whose parameters were estimated from the training sample, and further, compute mean squared errors of those forecasts. We search over a grid of regularization parameters and pick the one that minimizes the mean squared error on the validation sample. Since the estimation of model parameters uses data from the training sample alone, the validation procedure experiments an out-of-sample test of those models. Lastly, we evaluate the chosen model's predictive performance

Figure 9. Sample Split
This figure shows how we split the sample into disjoint training and validation subsamples in order to predict the selling activities of banks in each forecasting period of 2016Q1 through 2019Q4.



in the testing subsample, a real out-of-sample that is not involved in either model training or validation.

In order to forecast the selling activities of individual BHCs from 2016Q1 to 2019Q4, we adopt the following scheme of splitting the sample. In 2016Q1, we use the data of all BHCs from 2002Q2 to 2011Q4 as our initial training sample, and those from 2012Q1 to 2015Q4 as our initial validation sample. Moving forward along the forecast window, we recursively expand our training sample while shifting our validation window fixing its length of three years. See Figure 9 for a visual representation of this scheme.

5.1.3 Performance evaluation. To evaluate a model's performance for predicting the BHC-level selling activities, we calculate the out-of-sample R^2 as

$$R^2_{OS} = 1 - \frac{\sum_i \sum_{t \in \mathcal{T}_{test}} \left(y_{i,t} - \hat{g}(Z_{i,t-1})\right)^2}{\sum_i \sum_{t \in \mathcal{T}_{test}} (y_{i,t} - \bar{y}_{i,t})^2}, \tag{18}$$

where, $\mathcal{T}_{test}$ is the testing subsample and $y_{i,t}$ is the historical average Securities Sold / Assets of the i^{th} BHC prior to period t. This R^2_{OS} provides a panel-level assessment of the model performance by pooling together the prediction errors across all BHCs and all periods in the forecast window.

Another goal of the out-of-sample analysis is to identify the BHC characteristics that are important for predicting their selling activities in the subsequent quarter. Following Gu et al. (2020), we measure the variable importance of the p^{th} predictor as the reduction in panel predictive R^2 from setting all values of this predictor to zero, while fixing the remaining model estimates. We average this measure across all the training samples to obtain a single Variable Importance (VI_p) score for each predictor. We further normalize the VI_p values of all predictors to sum to one. Each machine learning model provides an independent assessment of the variables' importance. Thus the VI_p measure of a single predictor might vary across models.

5.2 Empirical Results

We forecast BHC-level securities sold to assets ratio using hundreds of bank characteristics as predictors. Same with the in-sample analysis, we consider the sales of total securities (All Securities), risky securities only (Risky Only), as well as safe securities only (Safe Only). Table 4 reports the out-of-sample predictive R^2_{OS} (in percentages) defined by equation (18) for all BHCs and quarters from 2016Q1 to 2019Q4.

The first row of Table 4 shows the R^2_{OS} for an OLS model using the BHC characteristics studied in the in-sample analysis as predictors. Those preselected predictors can barely forecast bank selling activities out-of-sample, and the R^2_{OS} is 1.23% for All Securities. Interestingly, such a model does a slightly better job at predicting the risky securities sales, producing an R^2_{OS} of 1.48%, than for the safe securities sales, which has an R^2_{OS} of -1.66%.

Linear combinations of a small number of preselected BHC characteristics cannot summarize all the predictive information one can obtain from the Y9-C filings. Jointly considering a broader set of BHC characteristics and using machine learning models substantially improve the R^2_{OS}. The second row of Table 4 shows that by regressing the bank selling activities on hundreds of BHC characteristics with a penalty, ENet improves the R^2_{OS} to 12.01% for all securities, 2.20% for risky securities only, and 14.94% for safe securities only. Further, GBRT, which accounts for nonlinear interactions of predictors, raise the R^2_{OS} for the three types of securities to 14.33%, 8.82%, and 17.70%, respectively, as shown in the third row of Table 4.

An important takeaway from Table 4 is that the prediction of BHCs' risky and safe securities sales benefit from different features of the model. For risky securities, the inclusion of hundreds of BHC characteristics only marginally increase the R^2_{OS} by 0.72% (comparing

Table 4. Out-of-sample Predictive R^2_{OS}
This out-of-sample predictive R^2_{OS} (in percentages) are constructed following equation (18). The OLS model use the small number of pre-selected ex ante BHC characteristics as predictors. The two machine learning approaches, ENet and GBRT are built upon hundreds of BHC characteristics. The definition and description of the BHC characteristics are presented in the Appendix.

	All Securities	Risky Only	Safe Only
OLS	1.23	1.48	-1.66
ENet	12.01	2.20	14.94
GBRT	14.33	8.82	17.70

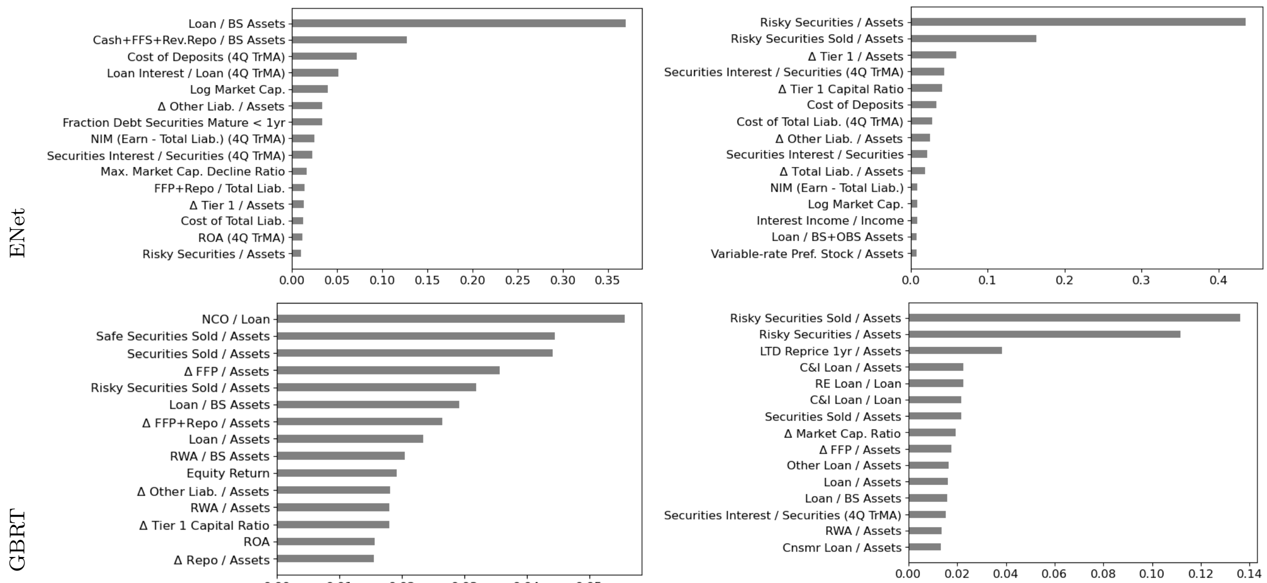
ENet to OLS). However, accounting for nonlinearity and predictor interactions improve the R^2_{OS} by three times (comparing GBRT to ENet). On the contrary, for predicting safe securities sales, the inclusion of more BHC characteristics substantially increases the R^2_{OS} by 16.60%, whereas the incorporation of nonlinear interactions of predictor only improves the R^2_{OS} by a 2.76%.

In sum, consistent with our finding in Section 4, selling activities of risky securities are less predictable than those of safe securities, reflected by the fact that the maximum R^2_{OS} we can achieve for the latter is much higher for the former. More interestingly, there are fewer relevant predictors for risky securities sales, and nonlinearity plays a big role. In comparison, more BHC characteristics carry useful information for predicting safe securities sales, and the predictive relationships are straightforward that even linear combinations of those predictors are sufficient for achieving good predictive performance.

Next, we investigate the importance of individual BHC characteristics for forecasting bank selling activities while simultaneously controlling for all the other characteristics. As described in Section 5.1.3, for a given machine learning model, the importance of a predictor is measured by the reduction in panel R^2 from setting all values of the predictor to zero.

Following Gu et al. (2020), we plot two figures to show the variable importance. Figure 10 reports the VI for the top-15 most influential BHC characteristics in the two machine learning models, ENet and GBRT. Two out of the three security types (all and risky) are presented in columns (a) and (b), respectively. We exclude the Safe Securities column from this figure because it is very similar to All Securities. In Figure 11, we present all BHC characteristics in descending order of their overall importance rank, constructed as the sum of their model-specific importance ranks. The color gradient within each column shows the

Figure 10. Variable Importance Across Models: Top-15 Most Influential
The Variable Importance, IV, is constructed following Section 5.1.3 and averaged across all training samples. For each machine learning model, the variable importance of all predictors are normalized to sum to one. Two out of the three security types (all and risky) are presented in columns (a) and (b), respectively. We exclude the Safe Securities column from this figure because it is very similar to All Securities.



(a) All Securities

(b) Risky Only

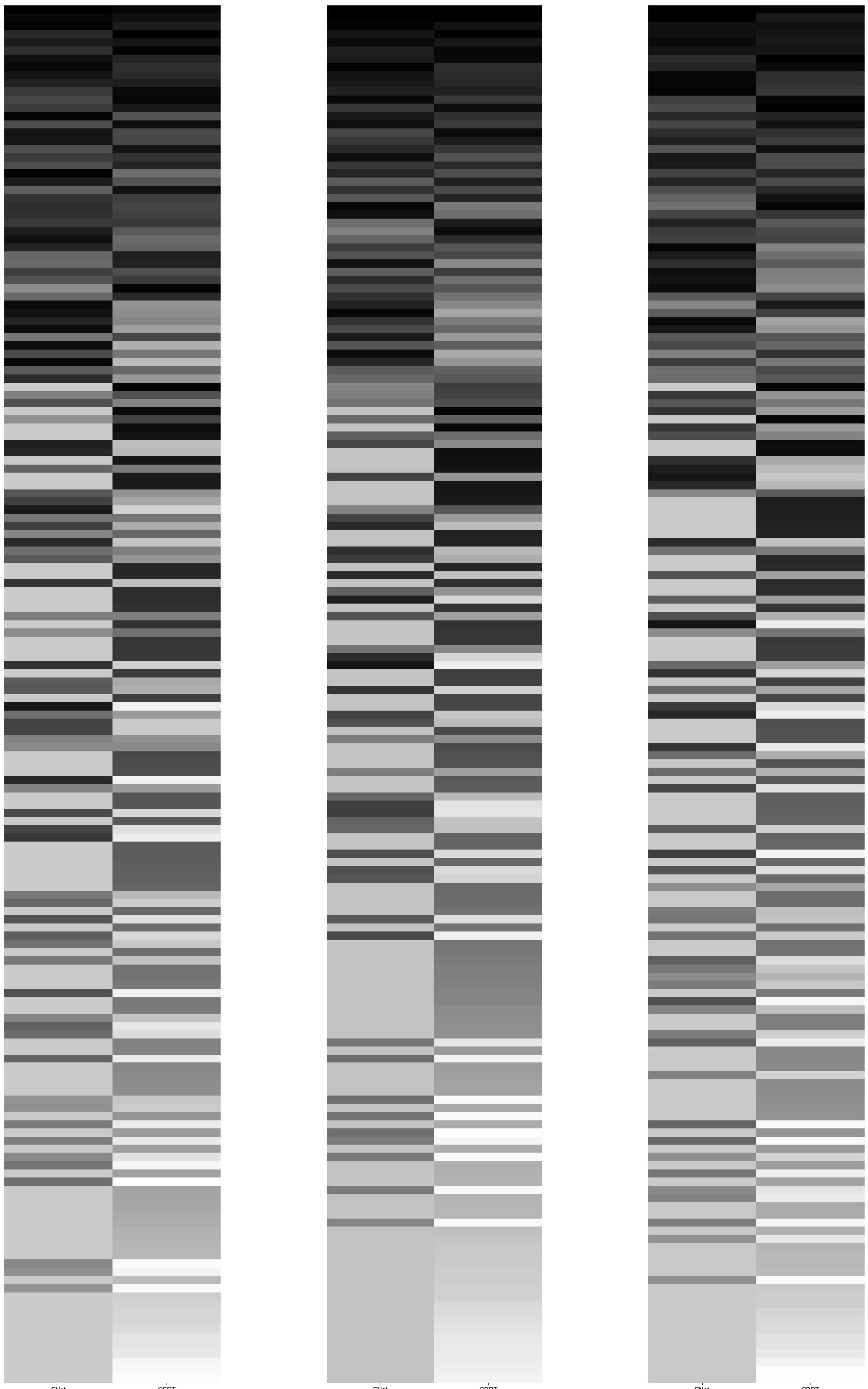
variables' importance rank in the corresponding model.

Figure 10 and Figure 11 show a certain degree of agreement among models regarding the most and least important influential BHC characteristics in predicting the selling activities of a given type of assets. For all securities, the machine learning models picks several different set of predictors compared to the ones we pre-selected in Section 4. These include the relative size of off-balance exposures (OBS Assets / BS+OBS Assets), bank size as measured by Log Market Cap., and the share of securities maturing within the next year (Fraction Debt Securities Mature $<$ 1yr). This latter finding makes sense given that, all else equal, maturing securities will disappear from the balance sheet and would therefore look like a sale from our perspective.

For risky securities, the most influential predictors for the selling activities of risky securities include the some of the ones we pre-selected in Section 4 (e.g., Risky Securities Sold / Assets; Δ FFP / Assets; Δ Tier 1 / Assets). Some chosen variables are modified versions of the variables from Section 4 (e.g., Cost of Deposits instead of Cost of Funds).

Figure 11. Variable Importance Across Models: All Variables

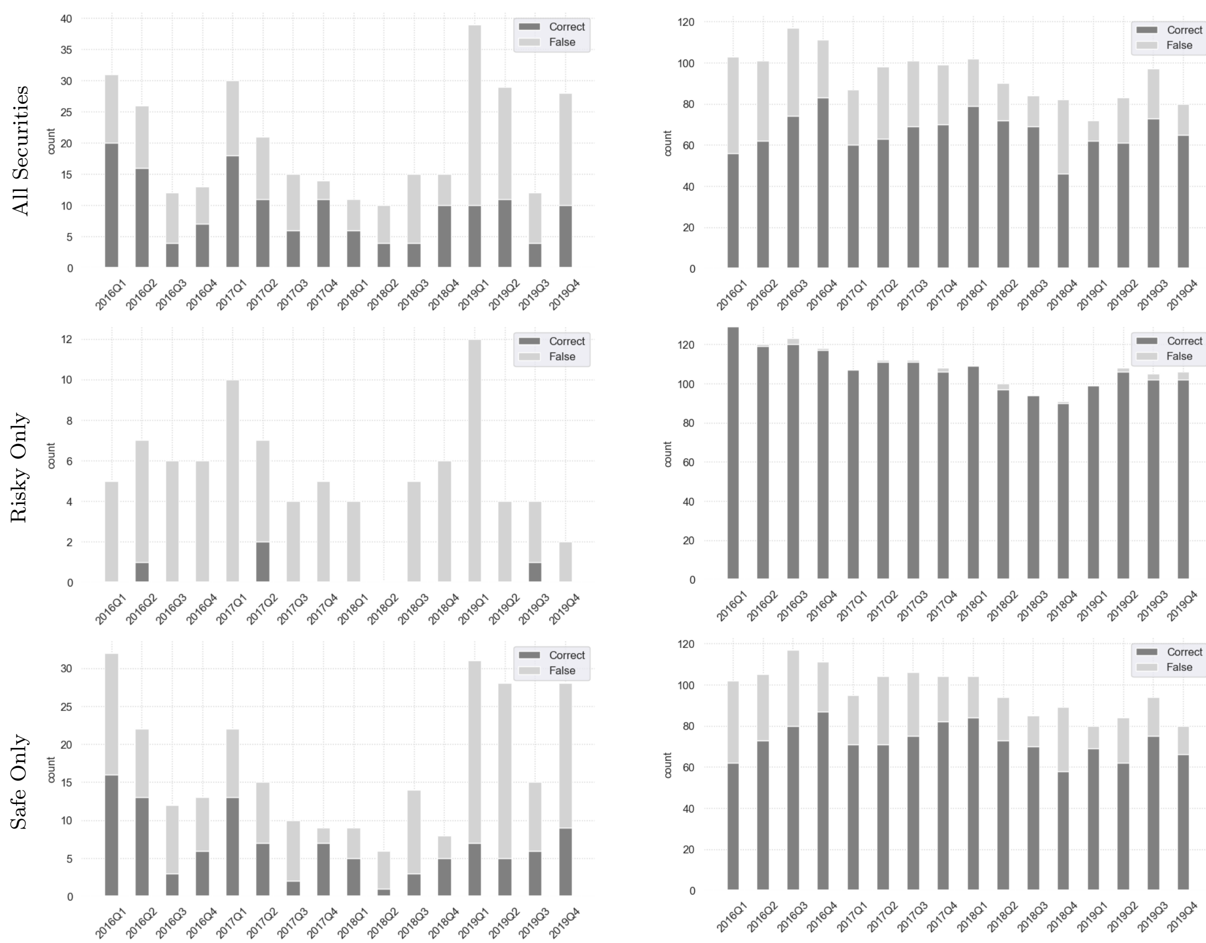
The overall importance ranks of the BHC characteristics are constructed as the sum of their importance rank from all models, measuring their overall contribution to predicting bank selling activities. The color gradients within columns indicate the model-specific variable importance of the characteristics. Characteristics are ordered such that the most influential predictors are on the top.e omit the specific variable labels because they would not be readable and the point of this figure is to visually represent how variable importance differs across models and selling measures.



(a) All Securities (b) Risky Only (c) Safe Only

The machine learning models also picks new predictors. These address the portfolio shares in more detail (e.g., Risky Securities / Assets; C&I Loan / Assets; RE Loan / Loan), the average interest return on securities that may proxy for riskiness (Securities Interest / Securities), the amount of long-term debt that is maturing soon (LTD Repice 1yr / Assets), and measures of net interest margin.

Figure 12. Accuracy in Predicting Relatively Large Sales of Securities
The large sales of securities are defined as sales with Securities Sold / Assets greater than 0.6%. A BHC is predicted to have large securities sales if its Securities Sold / Assets is predicted to be greater than the same threshold by any of the considered models. In column (a), the bars counts, in each quarter, the number of BHCs that actually have a higher than threshold sales. Banks that are correctly predicted to have large securities sales are colored by dark-gray. Bars in column (b) counts the number of BHCs that do not have large securities sales, and we again use dark-gray to mark the correct predictions. The three asset types are presented separately in the top, middle, and bottom panels.



(a) Predict sales

(b) Predict no sales

According to the theoretical framework in Greenwood et al. (2015), selling securities is one of the channels through which banks retrace the increase of leverage caused by adverse shocks to their asset values. Depending on the assets' liquidity, the securities sold have a price impact that causes spillover losses, which are even amplified through a second-round spillover effect if the system is aggregately vulnerable (Duarte and Eisenbach, 2018). Our study would be valuable for monitoring the indirect contagion if we can precisely forecast whether a BHC will sell a large fraction of its securities in the subsequent quarter or not. A BHC is predicted to have large securities sales in a given quarter if its Securities Sold / Assets is predicted to be greater than 0.6% by any of the considered models. Figure 12 reports, for each quarter, the models' joint correctness in predicting the "sales" and "no sales" in columns (a) and (b), respectively. Specifically, the bars in column (a) count, in each quarter, the number of BHCs whose Securities Sold / Assets are actually higher than the threshold. Banks that are correctly predicted to have a higher than threshold sales are colored by dark-gray. In column (b), the bars count the number of BHCs with Securities Sold / Assets lower than the threshold in each quarter, and we again use dark-gray to mark those correct predictions.

Figure 12 shows that, across all years, large securities sales are low-frequency events: fewer than 40 BHCs out of 200 every quarter. Further, such events are even rarer if we focus on the risky securities only: no more than 12 BHCs out of 200 every qurater. Such events are typically hard to predict, thus, no models can forecast large risky securities sales with satisfactory precision. The middle panel of column (a) shows that the models can only correctly predict a few large risky securities sales in 2016Q2, 2017Q2, and 2019Q3. In contrast, the models can find out almost all banks that will not sell a large proportion of their risky securities. The large sales of all securities and safe securities are more predictable than those of risky securities only. We observe more correct predictions (in dark gray) in the top and bottom panels of column (a) than in the middle panel on the same column.

6 Conclusion

In this paper, we study observed bank sales of securities in the data. To do so, we develop a method to measure securities selling activity by banks using publicly available data from regulatory filings. This method relies on the fact that banks are required to report both book values and market values for the bulk of their securities holdings. Our analysis proceeds in three broad steps. First, we document a set of stylized empirical facts regarding bank selling. Second, we establish empirical relationships between selling and other bank-level outcomes, which allow us to better understand the factors that are associated with bank selling. Third, we use machine learning techniques to assess the extent to which bank security sales can be predicted out-of-sample and which ex ante factors are important in doing so.

The contributions from our paper are threefold. First, we provide a new set of empirical facts regarding bank selling of securities. We hope that these insights and estimates can be used in future research to develop richer structural models of fire sales in the banking sector. Second, our out-of-sample predictions of bank selling could be used as an additional monitoring tool for indirect contagion. These forecasts would complement existing measures of indirect contagion risk such as those of Duarte and Eisenbach (2018). Third, we believe that our predictive model of bank selling could be used to forecast hypothetical bank selling activity in annual regulatory bank stress testing exercises.

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A Bank Holding Company Data

This section describes how we construct our sample of BHCs and also how we construct consistent time series variables from the Federal Reserve FR Y-9C.

For the primary data source, we utilize bank holding company (BHC) data collected by the Federal Reserve through the *Consolidated Financial Statements for Holding Companies* (FR Y-9C). Raw data are downloaded from the Federal Reserve of Chicago website (https://chicagofed.org/banking/financial-institution-reports/bhc-data). Throughout the description of the dataset, we use the terms "BHCs" and "banks" interchangibly to refer to the entities in this dataset. The RSSD ID is the primary and unique identifier assigned to each BHC.

The FR Y-9C data broadly provides balance sheet and income statement information on a quarterly basis. Of particular use in this study, it provides a detailed breakdown of securities holdings both in the banking book and trading book (Schedules HC-B and HC-D). We are also able to see contributions of these assets to regulatory ratios (Schedule HC-R).

Onto the FR Y-9C dataset, we merge equity returns, prices, and shares outstanding from CRSP using the FRBNY CRSP-FRB Link dataset (https://www.newyorkfed.org/research/banking_research/datasets.html). This dataset, which is maintained by Federal Reserve Bank of New York, links PERMCOs from CRSP to RSSD IDs from the FR Y-9C data.

Forming Our Sample

We must filter the raw FR Y-9C data in order to present an accurate and consistent description of BHC selling over time. To do so, we drop BHC subsidiaries whose assets are already captured in their parent's filings, nontraditional BHCs, and small BHCs that do not file frequently with sufficient detail. In the remainder of this section we provide more details for this process including the names and mnemonics of the specific variables used.

We identify observations of BHC subsidiaries whose parents also report data using the Financial High Holder ID (RSSD9364). We only drop a given BHC's observations if we observe that its financial high holder also reports data in the FR Y-9C. By doing so, we avoid double counting assets.

We identify nontraditional banks in two steps. First, we identify those with non-positive C&I loans plus real estate loans, non-positive deposits, consumer loans above 50% of total loans, or missing capital ratios. Second, we select specific large institutions that entered the FR Y-9C data only after the Financial Crisis of 2008. These institutions (RSSD IDs) are AIG (1562176), American Express (1275216), Discover Financial Services (3846375), Goldman Sachs (2380443), Metlife (2945824), and Morgan Stanley (2162966). We drop these institutions from our sample and analysis because they do not represent the type of traditional bank that we aim to study.

We identify small BHCs as those that ever have non-missing values for total assets as reported on the FR Y-9SP form (BHSP2170). Only BHCs above a specified asset-size threshold are required to file form FR Y-9C. BHCs below the threshold are required to file the less-detailed FR Y-9SP on a semi-annual basis. The asset-size threshold for the FR Y-9C has increased over time from $150 million to $500 million in 2006Q1, from $500 million to $1 billion in 2015Q1, and from $1 billion to $3 billion in 2018Q3.[2] By removing BHCs that switch to filing the FR Y-9SP at some point, we ensure that BHCs only drop out of our sample if they fail, merge with another BHC, or are acquired. We are also effectively imposing a minimum size limit on BHCs in our analysis.

Constructing Consistent Time Series

In this section, we describe how we construct our variables using data from the FR Y-9C. The FR Y-9C form has changed over time, and these changes mostly include the addition of new time series. Many times, however, the new time series replace older (and potentially less granular) versions of the same line item. As such, it is necessary to stitch together multiple mnemonics in order to construct a consistent time series. In Tables A.1 and A.2, we list the specific FR Y-9C series used in each variable.

[2]See the description of form FR Y-9C on the Federal Reserve website (https://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDal8cbqnRxZRg==)

Table A.1. Bank Holding Company Main Variables

Name	Description	Period	Formula Using FR Mnemonics
Tangible Assets	Total assets minus total intangible assets	Until 2018Q1	BHCK2170 - BHCK3163 - BHCK0426
		From 2018Q2	BHCK2170 - BHCK2143
Total Assets	Total assets	Entire	BHCK2170
Loans	Total loans and leases, net of unearned income	Entire	BHCK2122
Securities	Risky Securities plus Safe Securities	See Table A.2.	
Risky Securities	Private MBS, ABS, SFP, Other Debt, Equities, and Nonfed. Govt.	See Table A.2.	
Safe Securities	Agency MBS, U.S. Treasuries, and U.S. Govt. Agency Obligations	See Table A.2.	
Trading Securities	Risky Securities plus Safe Securities reported on scheduled HC-D (Trading Assets and Liabilities)	See Table A.2.	
Cost of Funds	Interest Expense divided by average ST Debt	See other definitions within this table	
ST Debt	Deposits plus FFP & Repo	See other definitions within this table	
Deposits	Deposits in domestic or foreign offices	Entire	BHDM6631 + BHDM6636 + BHFN6631 + BHFN6636
FFP & Repo	Federal funds purchased and securities sold under agreements to repurchase	Until 2001Q4	BHCK2800
		From 2002Q1	BHDMB993 + BHCKB995
FFP	Federal funds purchased in domestic offices	From 2002Q1	BHDMB993
Repo	Securities sold under agreements to repurchase	From 2002Q1	BHCKB995
Interest Expense	Interest on deposits plus expense on federal funds purchased and securities sold under agreements to repurchase	Until 2016Q4	BHCKA517 + BHCKA518 + BHCK6761 + BHCK4172 + BHCK4180
		From 2017Q1	BHCKHK03 + BHCKHK04 + BHCK6761 + BHCK4172 + BHCK4180
Tier 1 Capital Ratio	Tier 1 Capital divided by Risk-weighted Assets	Until 2014Q4	BHCK7206
		From 2015Q1	max(BHCA7206, BHCW7206)
Tier 1 Leverage Ratio	Tier 1 Capital divided by average Total Assets	Until 2014Q4	BHCK7204
		From 2015Q1	BHCA7204
Tier 1 Capital	Tier 1 capital	Until 2014Q4	BHCK8274
		From 2015Q1	BHCA8274
Net Charge-off Rate	Charge-offs minus Recoveries divided by average Loans	See other definitions within this table	
Charge-offs	Total charge-offs on loans and leases	Entire	BHCK4635
Recoveries	Total recoveries on loans and leases	Entire	BHCK4605
Unrealized Gain Return	Unrealized Gains divided by average Securities	See other definitions within this table	
Unrealized Gains	Sum of unrealized gains across security types	Computed from securities holdings, see section 2	
ROA	Net Income divided by average Total Assets	See other definitions within this table	
Net Income	Net income (loss) attributable to holding company	Entire	BHCK4340
Unuse. Comm.	Sum of unused commitments reported on Schedule HC-L (Derivatives and Off-Balance-Sheet Items)	Until 2009Q4	BHCK3814 + BHCK3815 + BHCK3816 + BHCK6550 + BHCK3817 + BHCK3818
		From 2010Q1	BHCK3814 + BHCJ455 + BHCKJ456 + BHCK3816 + BHCK6550 + BHCK3817 + BHCKJ457 + BHCKJ458 + BHCKJ459
Fin. Standby LOC	Financial standby letters of credit and foreign office guarantees	Entire	BHCK6566
Perform. Standby LOC	Performance standby letters of credit and foreign office guarantees	Entire	BHCK6570
Comm. LOC	Commercial and similar letters of credit	Entire	BHCK3411
Cash	Cash and balances due from depository institutions	Entire	BHCK0081 + BHCK0395 + BHCK0397
FFS & Rev. Repo	Federal funds sold and securities purchased under agreements to resell	Until 2001Q4	BHCK1350
		From 2002Q1	BHDMB987 + BHCKB989
FFS	Federal funds sold in domestic offices	Entire	BHDMB987
Rev. Repo	Securities purchased under agreements to resell	Entire	BHCKB989

Table A.2. Bank Holding Company Detailed Security Holdings Variables

Name	Schedule	Value	Period	Formula Using FR Mnemonics
U.S. Treasuries	HC-B	AC	Entire	BHCK0211 + BHCK1286
	HC-B	FV	Entire	BHCK0212 + BHCK1287
	HC-D	FV	Until 2007Q4	BHCK3531
			From 2008Q1	BHDM3531
U.S. Govt. Agency Obligations	HC-B	AC	Until 2018Q1	BHCK1289 + BHCK1294 + BHCK1291 + BHCK1297
			From 2018Q2	BHCKHT50 + BHCKHT52
	HC-B	FV	Until 2018Q1	BHCK1290 + BHCK1295 + BHCK1293 + BHCK1298
			From 2018Q2	BHCKHT51 + BHCKHT53
	HC-D	FV	Until 2007Q4	BHCK3532
			From 2008Q1	BHCM3532
Agency MBS	HC-B	AC	Until 2009Q1	BHCK1698 + BHCK1703 + BHCK1701 + BHCK1706 + BHCK1714 + BHCK1718 + BHCK1716 + BHCK1731
			2009Q2 through 2010Q4	BHCKG300 + BHCKG304 + BHCKG324 + BHCKG302 + BHCKG306 + BHCKG326 + BHCKG312 + BHCKG316 + BHCKK150 + BHCKG314 + BHCKG318 + BHCKK152
			From 2011Q1	BHCKG300 + BHCKG304 + BHCKK142 + BHCKKX52 + BHCKG302 + BHCKG306 + BHCKK144 + BHCKKX54 + BHCKG312 + BHCKG316 + BHCKK150 + BHCKG314 + BHCKG318 + BHCKK152
	HC-B	FV	Until 2009Q1	BHCK1699 + BHCK1705 + BHCK1702 + BHCK1707 + BHCK1715 + BHCK1719 + BHCK1717 + BHCK1732
			2009Q2 through 2010Q4	BHCKG301 + BHCKG305 + BHCKG325 + BHCKG303 + BHCKG307 + BHCKG327 + BHCKG313 + BHCKG317 + BHCKK151 + BHCKG315 + BHCKG319 + BHCKK153
			From 2011Q1	BHCKG301 + BHCKG305 + BHCKK143 + BHCKKX53 + BHCKG303 + BHCKG307 + BHCKK145 + BHCKKX55 + BHCKG313 + BHCKG317 + BHCKK151 + BHCKG315 + BHCKG319 + BHCKK153
	HC-D	FV	Until 2007Q4	BHCK3534 + BHCK3535
			2008Q1 through 2009Q1	BHCM3534 + BHCM3535
			2009Q2 through 2010Q4	BHCKG379 + BHCKG382 + BHCKG380
			From 2011Q1	BHCKG379 + BHCKK197 + BHCKG380
Nonfed. Govt.	HC-B	AC	Entire	BHCK8496 + BHCK8498
	HC-B	FV	Entire	BHCK8497 + BHCK8499
	HC-D	FV	Until 2007Q4	BHCK3533
			From 2008Q1	BHDM3533
Equities	HC-B	AC	Until 2017Q4	BHCKA510
			From 2018Q1	BHCKA510 + BHCKJA22
	HC-B	FV	Until 2017Q4	BHCKA511
			From 2018Q1	BHCKA511 + BHCKJA22
	HC-D	FV	From 2008Q1	BHCKF652 + BHCKF653