# Securities Portfolio Management in the Banking Sector*

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**Abstract**

We develop a method to measure the securities purchasing and selling activity of banks using publicly available data from regulatory filings. Using this data, we document stylized empirical facts and explain securities portfolio management through the lens of contemporaneous balance sheet movements. When focusing on balance sheet changes that are exogenous from the bank's perspective, we find that deposit shocks have the greatest explanatory power. We also find that banks only sell securities to meet deposit withdrawals when cash holdings are low and that, contrary to expectation, only well-capitalized banks sell their risky securities in these cases. Overall, our findings demonstrate unintended consequences on bank securities management from the post-GFC changes in bank regulation and provide guidance for modeling the risk of financial fire sales in regulatory stress testing exercises.

**Keywords:** indirect contagion, systemic risk, macroprudential supervision

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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 two broad steps. First, we document a set of stylized empirical facts regarding bank selling. Second, we establish empirical relationships between selling and contemporaneous balance sheet movements in order to understand the factors associated with bank selling.

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 numerous regressions to isolate and quantify the impact of contemporaneous balance sheet movements on bank selling activity. Our first key finding is that deposit shocks have the greatest explanatory power among balance sheet changes that are exogenous from the bank perspective. Further, the responses are asymmetric: banks purchase 22 cents in response to a deposit inflow of $1 while they only sell 12 cents to fund an outflow. Focusing on risky securities (e.g., ABS), we find that banks symmetrically purchase or sell 5–6 cents in response to deposit flows.

The above findings are found using our full sample of large banks during the period 2001–2019, and we next investigate the bank-level characteristics or factors that influence securities management responses to deposit shocks. Here, we find that only banks with low cash holdings sell securities upon deposit withdrawals. We also find that equity capitalization matters but not in the expected way. Only highly-capitalized banks sell risky securities in response to a deposit outflow.

The contributions from our paper are twofold. First, we provide a new set of empirical facts regarding the management of securities portfolios by banks. Specifically, we document the dominant role of deposit flows as well as the bank-level factors that affect the magnitude of the responses. These results point to unintended consequences of the post-GFC changes in bank regulation. These changes have led banks to hold more cash, which implies that the degree of large-scale selling of securities from the banking sector will be lower moving forward. However, the fact that banks are also now more highly capitalized suggests that they will sell more risky securities when they do respond to funding shock with security sales. Given the potential for large negative price impacts from selling risky securities in times of market distress, this implies that the banking sector may contribute more to the risk of indirect contagion risk moving forward.

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

**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.

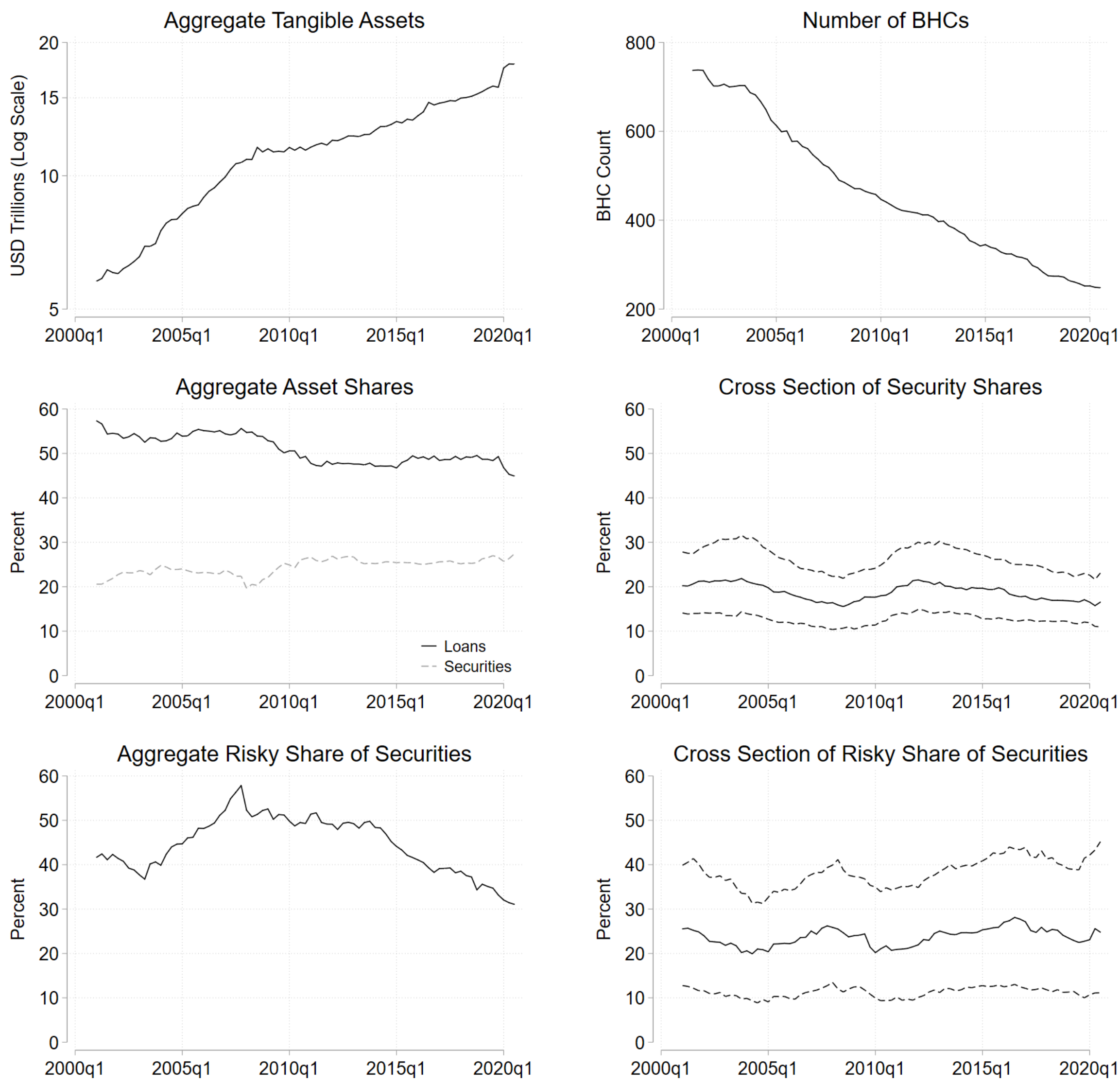
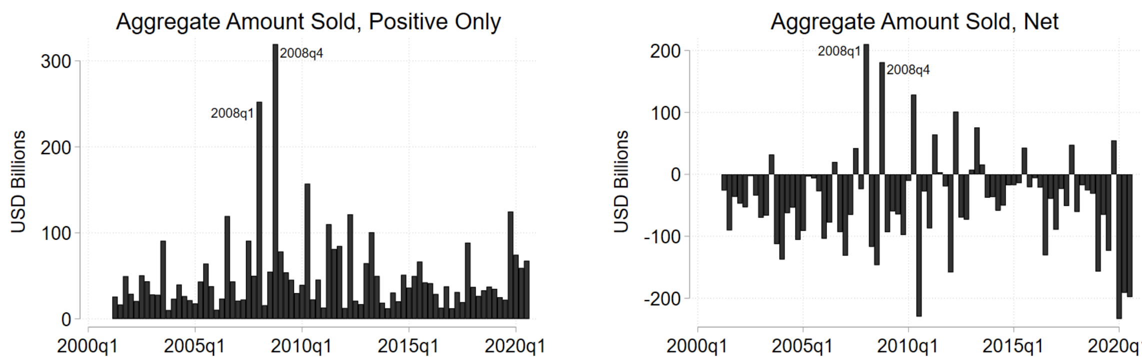


**Figure 2.** Bank Holding Company Securities Selling in Aggregate

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.



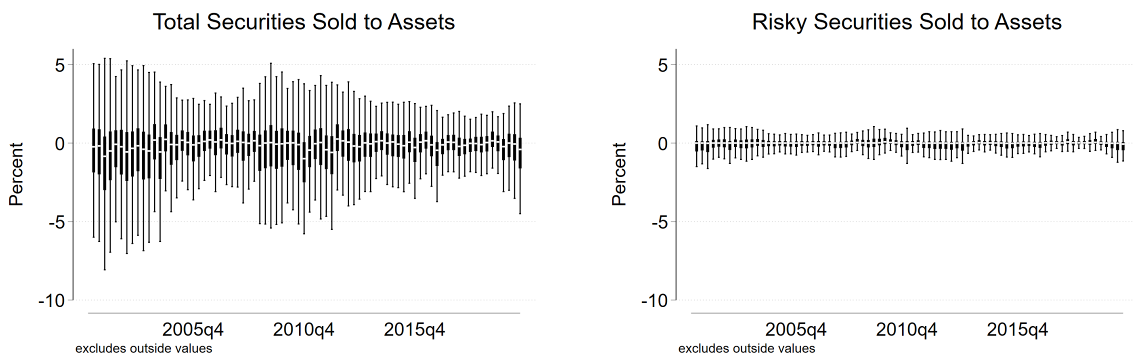

$200 billion. The fourth quarter observation in particular make sense given that this was the quarter in which the financial system was under significant distress and there was significant anecdotal evidence of fire sale activity. In the right panel, we report the sum of all net selling flows, which 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-

**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.




backed securities) tend to be much smaller in comparison. As such, we can infer that BHCs 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

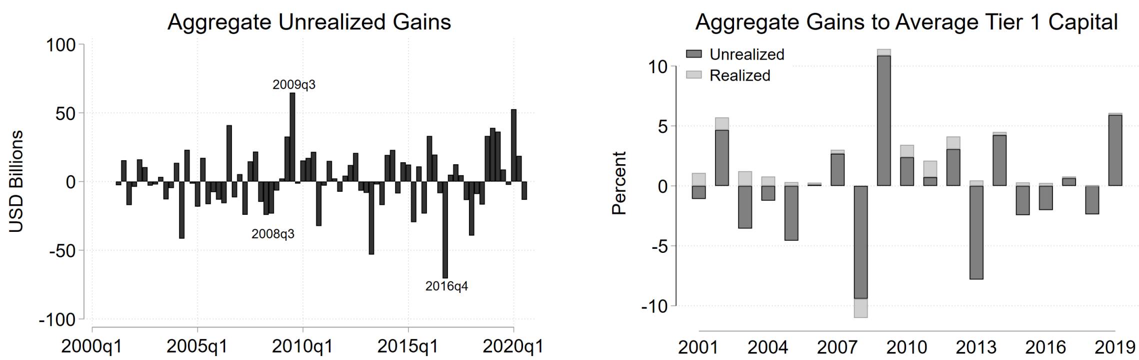
**Figure 4.** Composition of Bank Holding Company Sales

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.


losses do not generally affect a bank's regulatory capital calculations (Beatty and Liao, 2014), 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

**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.




panel of figure 5, we put both unrealized gains and realized gains into perspective by dividing 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 Empirical Analysis

Our empirical analysis is grounded from a balance sheet perspective. We view banks as making their investment and financing decisions to maximize an objective function subject to constraints including balance sheet identity:

$$\Delta Assets = \Delta Debt + \Delta Equity. \tag{14}$$

This balance sheet identity can be decomposed as follows:

$$\Delta Assets = \underbrace{\Delta Loans + \Delta Cash + \Delta Securities + \Delta OtherAssets}_{Endogenous} \tag{15}$$

$$\underbrace{+\Delta UnusedCommit + NetChargeoff + \Delta SecurityValues}_{\approx Exogenous}$$

$$\Delta Debt = \underbrace{\Delta FFP + \Delta Repo + \Delta OBM}_{Endogenous} + \underbrace{\Delta Deposits}_{\approx Exogenous} \tag{16}$$

$$\Delta Equity = \underbrace{\Delta BusiComb - NetEquityPayout}_{Endogenous} + \underbrace{\Delta RetainedEarnings}_{\approx Exogenous} \tag{17}$$

where all of the above components can be directly measured in the data. Note that our measurement approach described in Section 2 allows us to separate changes in the holdings of securities from changes in their values. Our categorization of balance sheet movements into "exogenous" and "endogenous" is based on our subjective view of which items banks directly control. For example, banks actively choose whether to engage in short-term borrowing through the repo market. On other hand, banks may try to attract deposits but they cannot force depositors to do so.

For our analysis, we focus on the 36 large traditional BHCs with assets over \$50 billion at least in our period during our 2001–2019 sample. We do so in order to focus on banks with the largest security holdings both on an absolute and relative basis as these are the banks for which regulators and policymakers are most interested in understanding their securities management activities. We divide all variables by $Assets_{j,t-1}$ and then regress endogenous outcomes on the full set of exogenous variables:

$$\underbrace{y_{j,t}}_{Endogenous} = \beta_1 \Delta Deposits_{j,t} + \beta_2 \Delta UnusedCommit_{j,t} + \beta_3 NetChargeoff_{j,t} \tag{18}$$

$$+ \beta_4 UnrealizedLosses_{j,t} + \beta_5 \Delta EquityFromRE_{j,t} + \epsilon_{j,t}.$$

Given our balance sheet approach, this specification includes all variables measured in the same period.[1] Although our focus will be on changes in securities holdings, we are also inter-

[1] One may be interested in assessing which variables predict selling activity in the next period. In Appendix B, we find that such one-period-ahead predictability is limited even when using machine learning techniques.

ested in the relationships of the exogenous balance sheet movements with other endogenous outcomes such as new lending to provide helpful context.

**Table 1.** Summary Statistics

| | $N$ | Mean | SD | 1% | 10% | 50% | 90% | 99% |
|---|---|---|---|---|---|---|---|---|
| Securities Purchased | 2152 | 0.52 | 2.02 | -4.86 | -1.21 | 0.18 | 2.64 | 9.21 |
| Risky Securities Purchased | 2152 | 0.15 | 1.05 | -3.18 | -0.56 | -0.00 | 1.06 | 5.35 |
| Unreal. Losses Securities | 2152 | -0.00 | 0.23 | -0.73 | -0.27 | -0.00 | 0.26 | 0.78 |
| New Loans | 2152 | 0.56 | 4.52 | -14.40 | -2.73 | 0.11 | 3.70 | 25.69 |
| Δ Unuse. Comm. | 2152 | 0.52 | 3.63 | -16.00 | -1.63 | 0.39 | 2.73 | 19.57 |
| Net Chargeoffs | 2152 | 0.12 | 0.15 | -0.00 | 0.00 | 0.06 | 0.30 | 0.86 |
| New Cash | 2152 | 0.24 | 2.07 | -5.99 | -1.64 | 0.03 | 2.27 | 8.76 |
| New Other Assets | 2152 | 0.24 | 1.63 | -4.63 | -1.20 | 0.08 | 1.70 | 7.83 |
| Δ Deposits | 2152 | 1.61 | 4.29 | -7.40 | -1.77 | 0.91 | 5.28 | 26.97 |
| Δ FFP | 2024 | -0.01 | 0.88 | -3.36 | -0.73 | 0.00 | 0.76 | 3.43 |
| New Other Borrowing | 2152 | 0.21 | 2.11 | -5.92 | -1.97 | 0.05 | 2.57 | 8.13 |
| Net Equity Payout | 2152 | 0.00 | 0.64 | -2.62 | -0.69 | 0.10 | 0.39 | 2.39 |
| Δ Equity through RE | 2152 | 0.05 | 0.71 | -3.15 | -0.76 | 0.21 | 0.53 | 2.37 |

*Notes.* This table includes the summary statistics from our quarterly panel data that includes the 36 traditional bank holding companies with at least $50 billion of assets during our sample period of 2001–2019.

We present summary statistics for the variables in (15)–(17) in Table 1. Here we observe that most of these normalized variables are close to zero on average. An exception is the positive change in deposits, which reflects the fact that the banks in our sample increased their share of deposit funding throughout our sample period.

Before proceeding to our regression analysis, we further decompose deposit flows into their idiosyncratic and systematic components. To do so, we regress bank-level deposit growth on aggregate deposit growth and other predictive variables (Table 2). We consider the residuals from this regression to represent idiosyncratic deposit growth while the fitted value is the systematic component. One interesting takeaway from these findings is that the majority of quarterly variation in deposit growth for a given bank comes from the idiosyncratic component as demonstrated by the relatively low $R^2$ values. For our analysis specifically, we use the residuals and fitted values as determined from specification (5) but at the bank level, which allows for banks to have differing sensitivities in their deposit growth to aggregate fluctuations.

The results from running our benchmark specification in (18) are presented in Table 3. While we are most interested for this study in the results from the New Securities column, we

**Table 2.** Bank-level Deposit Growth: Systematic vs Idiosyncratic

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Lagged Bank-level Deposit Growth | | -0.056** | | | -0.062*** | | -0.062** |
| | | (-2.42) | | | (-2.61) | | (-2.51) |
| Agg. Comm. Bank Deposit Growth | | | 0.834*** | | 0.755*** | | |
| | | | (5.06) | | (4.51) | | |
| Δ Eff. Fed. Funds Rate | | | | -0.012*** | -0.009** | | |
| | | | | (-2.94) | (-2.10) | | |
| Constant | 0.022*** | 0.023*** | 0.008*** | 0.022*** | 0.010*** | 0.022*** | 0.023*** |
| | (16.77) | (16.08) | (2.76) | (16.92) | (3.47) | (17.10) | (16.39) |
| Quarter FE | No | No | No | No | No | Yes | Yes |
| $R^2$ | 0.000 | 0.003 | 0.015 | 0.008 | 0.021 | 0.072 | 0.077 |
| $N$ | 2044 | 2008 | 2044 | 2044 | 2008 | 2044 | 2008 |

*Notes.* In this table, we report the results from estimates of specification (2) Standard errors are heteroskedasticity-consistent. $t$-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

run these regressions separately for each endogenous variable in (15)–(17) to provide helpful context.

There are a few main takeaways from the results in Table 3. The first is that the majority of variation in securities activity can be attributed to idiosyncratic deposit shocks. We infer this not only from the large and statistically significant coefficients in Panel A but also from the variance decomposition presented in Panel B. The second is the responses of securities holdings to idiosyncratic deposit shocks are asymmetric: banks purchase 22 cents in response to a deposit inflow of $1 while they only sell 12 cents to fund an outflow. As a final point, it is interesting to note that all of the exogenous balance sheet movements together only explain around 20% of the observed variation in securities holdings. Therefore the majority of variation in securities holdings can be attributed to endogenous decisions of the bank (e.g., purchase securities with cash or sell securities to make a new loan).

Now that we have established the important role that deposit shocks play in securities holdings, we consider the composition of securities sold. Specifically, we run the regression in (3) separately for risky and safe securities as defined in Section 3. The results are presented in Table 4. In contrast to total securities, we find that banks tend to purchase or sell risky securities in the same proportion regardless of the direction of the deposit shock. In other words, changes in risky securities holdings do not display any asymmetry with respect to deposit shocks.

Next, we consider the potential impact of of bank on the response of securities hold-

**Table 3.** Benchmark Regression Results

Panel A: Coefficient Estimates

| | Assets | | | | Debt | | | Equity |
|---|---|---|---|---|---|---|---|---|
| | New Securities | New Loan | New Cash | New OA | New Repo | New FFP | New OBM | NEP |
| Δ Deposits (Idiosyncratic, Positive) | 0.224*** | 0.909*** | 0.213*** | 0.239*** | 0.030*** | -0.005 | 0.175*** | -0.034*** |
| | (9.38) | (9.98) | (8.59) | (11.39) | (3.45) | (-0.44) | (6.73) | (-3.81) |
| Δ Deposits (Idiosyncratic, Negative) | 0.120*** | -0.006 | 0.424*** | 0.065*** | -0.005 | -0.065*** | -0.116*** | 0.007 |
| | (3.92) | (-0.15) | (14.06) | (2.63) | (-0.43) | (-4.04) | (-3.40) | (1.03) |
| Δ Deposits (Systematic) | 0.184*** | 0.191*** | 0.352*** | 0.058** | 0.002 | -0.039*** | 0.040 | -0.011 |
| | (5.11) | (2.73) | (10.80) | (2.34) | (0.18) | (-3.20) | (1.30) | (-1.43) |
| Δ Unuse. Comm. | 0.008 | -0.852*** | -0.044*** | 0.010 | -0.000 | 0.000 | 0.017 | 0.005 |
| | (0.68) | (-19.77) | (-3.45) | (0.83) | (-0.00) | (0.02) | (1.01) | (1.48) |
| Net Chargeoffs | -0.168 | -3.425*** | 0.878*** | -0.131 | -0.169* | -0.353*** | -1.677*** | -0.092 |
| | (-0.62) | (-6.02) | (3.55) | (-0.60) | (-1.87) | (-3.17) | (-4.96) | (-0.70) |
| Unreal. Losses Securities | 0.498** | -0.008 | -0.197 | -0.260* | -0.182* | -0.153* | -0.500** | 0.269*** |
| | (2.02) | (-0.03) | (-1.20) | (-1.85) | (-1.85) | (-1.77) | (-2.57) | (5.17) |
| Δ Equity through RE | 0.014 | -0.109 | 0.010 | -0.027 | -0.009 | 0.015 | -0.237*** | 0.536*** |
| | (0.21) | (-0.94) | (0.17) | (-0.51) | (-0.27) | (0.46) | (-2.88) | (15.22) |
| Constant | 0.001 | 0.001 | -0.002** | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 |
| | (1.56) | (0.34) | (-2.45) | (-0.83) | (-0.06) | (0.76) | (0.01) | (1.57) |
| $R^2$ | 0.169 | 0.594 | 0.321 | 0.220 | 0.016 | 0.024 | 0.087 | 0.355 |
| $N$ | 2080 | 2080 | 2080 | 2080 | 2016 | 2016 | 2080 | 2080 |

Panel B: Variance Decomposition

| | Assets | | | | Debt | | | Equity |
|---|---|---|---|---|---|---|---|---|
| | New Securities | New Loan | New Cash | New OA | New Repo | New FFP | New OBM | NEP |
| Δ Deposits (Idiosyncratic, Positive) | 59.2 | 48.5 | 37.7 | 78.2 | 62.1 | 7.8 | 47.7 | 4.6 |
| Δ Deposits (Idiosyncratic, Negative) | 9.9 | 1.2 | 45.3 | 5.8 | 2.4 | 52.3 | 7.1 | 0.1 |
| Δ Deposits (Systematic) | 23.6 | 3.1 | 14.1 | 6.2 | 0.9 | 21.0 | 6.2 | 0.2 |
| Δ Unuse. Comm. | 5.7 | 44.3 | 1.6 | 9.2 | 13.7 | 0.6 | 17.3 | 0.2 |
| Net Chargeoffs | 0.6 | 2.8 | 1.0 | 0.2 | 5.5 | 12.6 | 17.5 | 0.4 |
| Unreal. Losses Securities | 0.9 | 0.0 | 0.0 | 0.3 | 15.1 | 3.8 | 1.0 | 1.4 |
| Δ Equity through RE | 0.1 | 0.1 | 0.3 | 0.2 | 0.3 | 2.0 | 3.1 | 93.1 |
| $R^2$ | 0.170 | 0.511 | 0.273 | 0.241 | 0.017 | 0.026 | 0.097 | 0.345 |
| $N$ | 2008 | 2008 | 2008 | 2008 | 1944 | 1944 | 2008 | 2008 |

*Notes.* In this table, we report the results from estimates of (18). Standard errors are heteroskedasticity-consistent. $t$-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ings to deposit shocks. For bank-specific relative characteristics, we focus on cash holdings, equity capital, and leverage. Cash holdings may affect selling decisions because a bank could theoretically meet deposit withdrawals using cash instead of selling securities. Equity capitalization and leverage may affect bank securities decisions given how such factors are related to bank distress. Theoretical models of bank selling tend to assume that banks consider their regulatory constraints in their securities selling decisions (e.g. Cont and Schaanning, 2019).

In Table 6, we present our findings on the impact of initial cash holdings. Our main takeaway is the securities selling response to a deposit outflow shock is effectively mitigated if a bank is holding relative little cash on its balance sheet. Specifically, we focus on the threshold of 4% cash-to-assets ratio based on the figure in Section 3. Related to this figure, we also include a post-2016 dummy in case the cash holding result is actually picking up the impact of the post-GFC banking regulation, which was nearly all phased in starting in 2016.

**Table 4.** New Securities: Risky vs Safe

| | New Securities | | |
|---|---|---|---|
| | Any Type | Risky Only | Safe Only |
| Δ Deposits (Idiosyncratic, Positive) | 0.218*** | 0.058*** | 0.155*** |
| | (8.71) | (3.70) | (7.52) |
| Δ Deposits (Idiosyncratic, Negative) | 0.127*** | 0.051*** | 0.051* |
| | (3.97) | (2.72) | (1.88) |
| Δ Deposits (Systematic) | 0.236*** | 0.103*** | 0.114*** |
| | (5.57) | (4.34) | (3.47) |
| Δ Unuse. Comm. | 0.018 | -0.002 | 0.021* |
| | (1.23) | (-0.17) | (1.65) |
| Net Chargeoffs | -0.087 | -0.258 | 0.140 |
| | (-0.32) | (-1.55) | (0.69) |
| Unreal. Losses Securities | 0.312 | -0.060 | 0.398* |
| | (1.26) | (-0.41) | (1.92) |
| Δ Equity through RE | -0.018 | -0.027 | -0.013 |
| | (-0.26) | (-0.62) | (-0.24) |
| Constant | 0.001 | 0.000 | 0.001 |
| | (0.64) | (0.20) | (0.79) |
| $R^2$ | 0.170 | 0.065 | 0.107 |
| $N$ | 2008 | 2008 | 2008 |

*Notes.* In this table, we report the results from estimates of (18). Standard errors are heteroskedasticity-consistent. $t$-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

However, this dummy is insignificant suggesting that cash holdings is the relevant factor, not changes in regulation.

**Table 5.** Impact of Beginning-of-Period Cash Holdings

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Deposits (Idiosyncratic, Positive) | 0.218*** | 0.191*** | 0.191*** | 0.181*** |
| | (8.71) | (5.27) | (7.26) | (4.98) |
| x Cash Ratio ≤ 4% | | 0.040 | | 0.013 |
| | | (0.86) | | (0.26) |
| x Post-2016 Dummy | | | 0.127*** | 0.077 |
| | | | (3.01) | (0.72) |
| x Cash Ratio ≤ 4% x Post-2016 Dummy | | | | 0.064 |
| | | | | (0.54) |
| Δ Deposits (Idiosyncratic, Negative) | 0.127*** | 0.067* | 0.126*** | 0.062 |
| | (3.97) | (1.81) | (3.62) | (1.44) |
| x Cash Ratio ≤ 4% | | 0.178*** | | 0.182*** |
| | | (4.04) | | (3.56) |
| x Post-2016 Dummy | | | 0.032 | 0.049 |
| | | | (0.72) | (0.97) |
| x Cash Ratio ≤ 4% x Post-2016 Dummy | | | | -0.006 |
| | | | | (-0.07) |
| Other Exo. Vars | Yes | Yes | Yes | Yes |
| $R^2$ | 0.170 | 0.178 | 0.175 | 0.183 |
| $N$ | 2008 | 2008 | 2008 | 2008 |

*Notes.* In this table, we report the results from estimates of (18) with additional terms. Standard errors are heteroskedasticity-consistent. $t$-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table 6.** Impact of Beginning-of-Period Bank Characteristics

Panel A: All Securities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Deposits (Idiosyncratic, Positive) | 0.218*** | 0.258*** | 0.210*** | 0.248*** |
| | (8.71) | (7.92) | (7.99) | (7.38) |
| x Cap Ratio ≤ 10% | | -0.105** | | -0.114*** |
| | | (-2.47) | | (-2.74) |
| x GFC Dummy | | | 0.063 | 0.190 |
| | | | (0.94) | (1.59) |
| x Cap Ratio ≤ 10% x GFC Dummy | | | | -0.108 |
| | | | | (-0.74) |
| Δ Deposits (Idiosyncratic, Negative) | 0.127*** | 0.129*** | 0.123*** | 0.119*** |
| | (3.97) | (3.31) | (3.76) | (3.04) |
| x Cap Ratio ≤ 10% | | -0.009 | | 0.005 |
| | | (-0.22) | | (0.10) |
| x GFC Dummy | | | 0.017 | 0.046 |
| | | | (0.23) | (0.39) |
| x Cap Ratio ≤ 10% x GFC Dummy | | | | -0.074 |
| | | | | (-0.55) |
| $R^2$ | 0.170 | 0.175 | 0.171 | 0.179 |
| *N* | 2008 | 2008 | 2008 | 2008 |

Panel B: Risky Securities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Deposits (Idiosyncratic, Positive) | 0.058*** | 0.057*** | 0.048*** | 0.049** |
| | (3.70) | (2.67) | (2.99) | (2.30) |
| x Cap Ratio ≤ 10% | | 0.003 | | -0.004 |
| | | (0.10) | | (-0.13) |
| x GFC Dummy | | | 0.087* | 0.156*** |
| | | | (1.90) | (2.64) |
| x Cap Ratio ≤ 10% x GFC Dummy | | | | -0.091 |
| | | | | (-1.16) |
| Δ Deposits (Idiosyncratic, Negative) | 0.051*** | 0.071*** | 0.049*** | 0.066*** |
| | (2.72) | (3.17) | (2.58) | (2.87) |
| x Cap Ratio ≤ 10% | | -0.067*** | | -0.061** |
| | | (-2.64) | | (-2.20) |
| x GFC Dummy | | | -0.004 | 0.017 |
| | | | (-0.09) | (0.27) |
| x Cap Ratio ≤ 10% x GFC Dummy | | | | -0.027 |
| | | | | (-0.36) |
| $R^2$ | 0.065 | 0.069 | 0.071 | 0.076 |
| *N* | 2008 | 2008 | 2008 | 2008 |

*Notes.* In this table, we report the results from estimates of (18) with additional terms. Standard errors are heteroskedasticity-consistent. $t$-statistics are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

# 5 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.

The contributions from our paper are twofold. First, we provide a new set of empirical facts regarding the management of securities portfolios by banks. Specifically, we document the dominant role of deposit flows as well as the bank-level factors that affect the magnitude of the responses. These results point to unintended consequences of the post-GFC changes in bank regulation. These changes have led banks to hold more cash, which implies that the degree of large-scale selling of securities from the banking sector will be lower moving forward. However, the fact that banks are also now more highly capitalized suggests that they will sell more risky securities when they do respond to funding shock with security sales. Given the potential for large negative price impacts from selling risky securities in times of market distress, this implies that the banking sector may contribute more to the risk of indirect contagion risk moving forward.

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.

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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 |

# B 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, 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).

## B.1 Methodology

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

$$\text{(Securities Sold / Assets)}_{i,t} = g(Z_{i,t-1}) + \epsilon_{i,t}, \tag{19}$$

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 (19) 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.

**B.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.

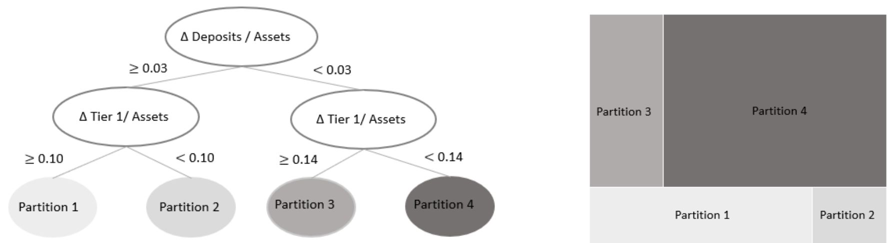
We start with a linear machine learning model, elastic net regression (ENet), for its simplicity. An ENet is prescribed to minimize the standard mean squared error made by the model, augmented with a regularization term that penalizes the total absolute values (L1 penalty) and squares (L2 penalty) of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

$$\mathcal{L}(\beta;\lambda,\alpha) = \underbrace{\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t+1}-\beta_0-\sum_{p=1}^{P}\beta_p z_{i,t}^{p}\right)}_{\text{mean squared error}} + \underbrace{\lambda(1-\alpha)\sum_{p=1}^{P}|\beta_p|}_{\text{L1 penalty}} + \underbrace{\lambda\alpha\sum_{p=1}^{P}\beta_p^2}_{\text{L2 penalty}}, \quad (20)$$

where $y$ represents the Securities Sold / Assets. An ENet involves two regularization parameters, $\lambda$ and $\alpha$: $\lambda$ governs the overall level of penalty. Without any regularization ($\lambda = 0$), ENet collapses to a standard OLS regression. $\alpha$ 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 ($\lambda$, $\alpha$), the ENet predicts bank security sales 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.

**Figure B.1.** 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.

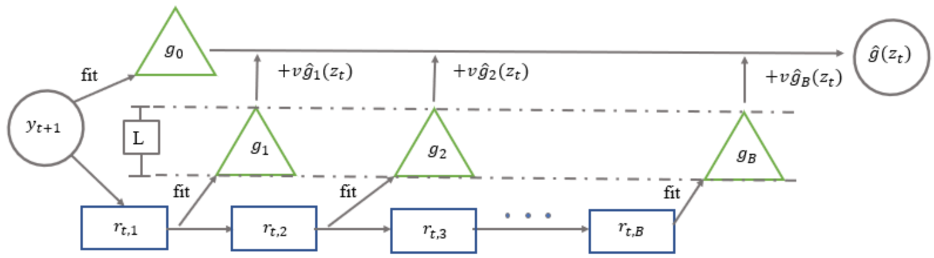



GBRT is a fully non-parametric approach that ensembles predictions from many trees. At a basic level, a tree "grows" in a sequence of steps (illustrated by Figure B.1): at each new "branch", the data left over from the preceding step are sorted into bins based on one of the predictors. The average outcome 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 $\theta_k$. 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 B.2, 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 "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 ($\lambda$, $\alpha$) 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.

**Figure B.2.** 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.

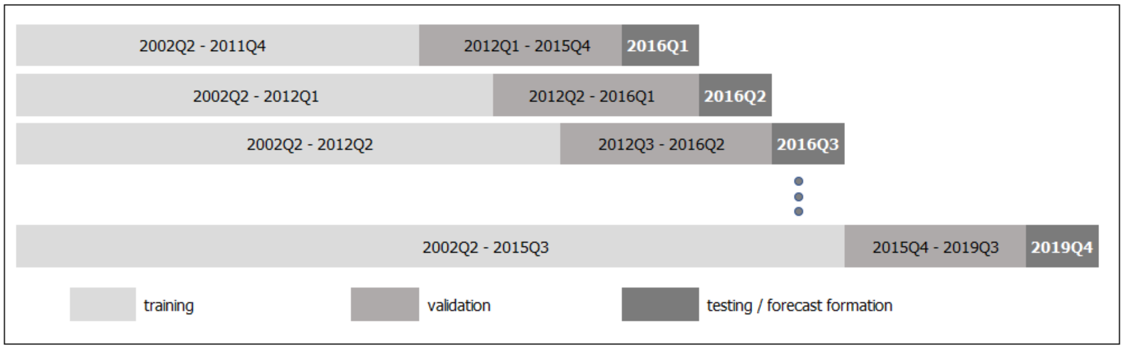



**B.1.2 Sample Splitting.** The regularization in machine learning prevents overfitting by penalizing the model flexibility. An over-regularized model tends to be overly simplified to approximate complex predictive relationships, whereas an under-regularized model will overfit the data resulting in a poor out-of-sample predictive performance. We choose the optimal regularization parameters, i.e., ($\lambda$, $\alpha$) 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 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

**Figure B.3.** 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.




years. See Figure B.3 for a visual representation of this scheme.

**B.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

$$R^2_{OS} = 1 - \frac{\sum_i \sum_{t \in \mathcal{T}_{test}} (y_{i,t} - \hat{g}(Z_{i,t-1}))^2}{\sum_i \sum_{t \in \mathcal{T}_{test}} (y_{i,t} - \bar{y}_{i,t})^2}, \tag{21}$$

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.

## B.2 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 B.1 reports the out-of-sample predictive $R^2_{OS}$ (in percentages) defined by equation (21) for all BHCs and quarters from 2016Q1 to 2019Q4.

The first row of Table B.1 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 B.1 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 B.1.

An important takeaway from Table B.1 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 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

**Table B.1.** Out-of-sample Predictive $R^2_{OS}$

This out-of-sample predictive $R^2_{OS}$ (in percentages) are constructed following equation (21). 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 |

$R^2_{OS}$ 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.

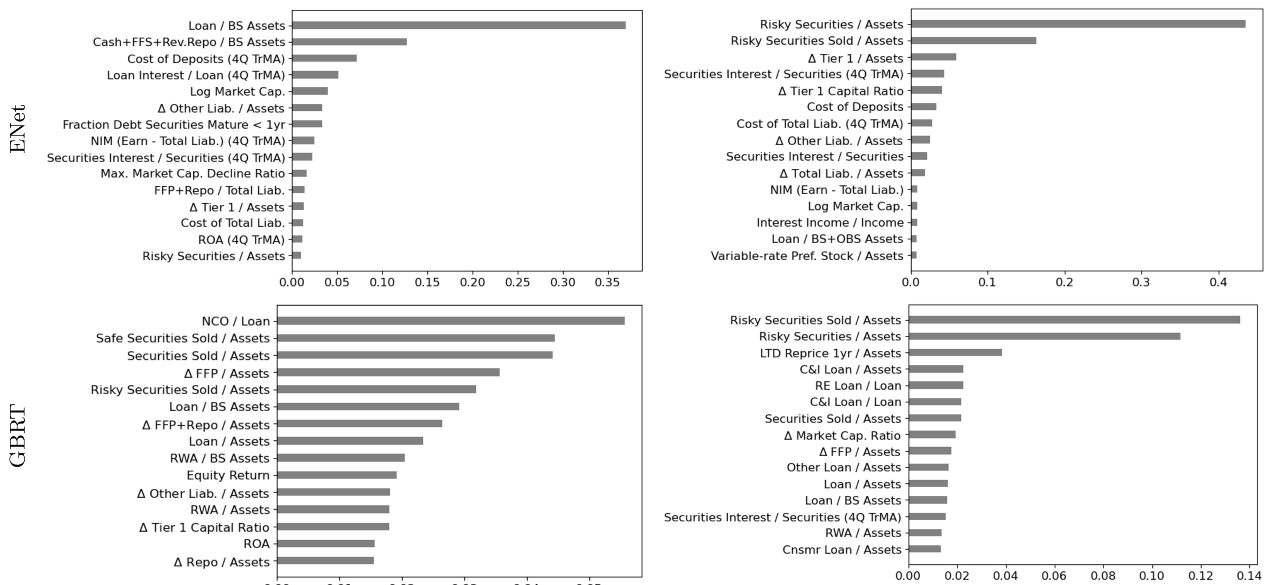
Next, we investigate the importance of individual BHC characteristics for forecasting bank selling activities while simultaneously controlling for all the other characteristics. As described in Section B.1.3, for a given machine learning model, the importance of a predictor is measured by the reduction 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 B.4 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 B.5, 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 variables' importance rank in the corresponding model.

Figure B.4 and Figure B.5 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

**Figure B.4.** Variable Importance Across Models: Top-15 Most Influential

The Variable Importance, $IV$, is constructed following Section B.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

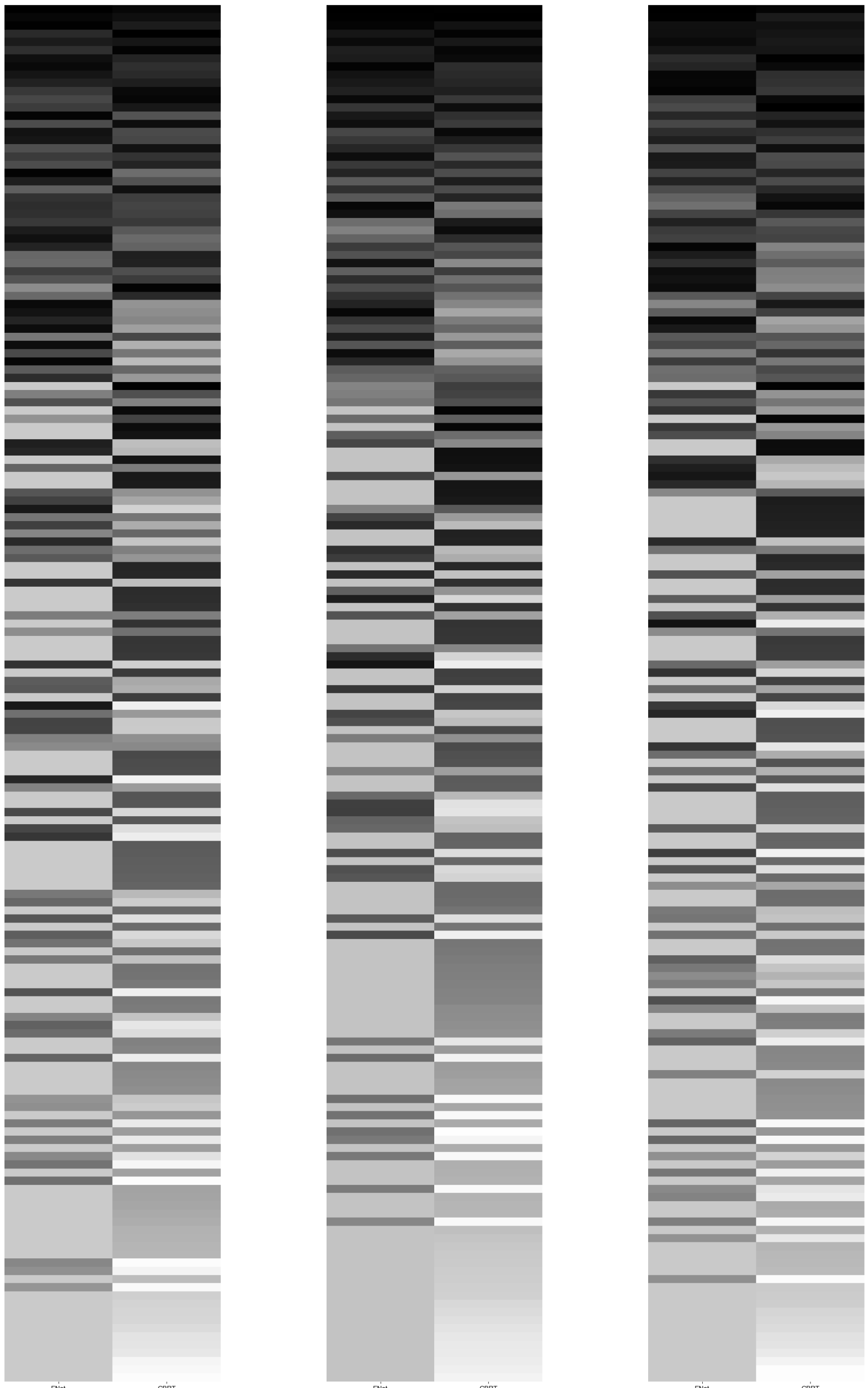
(Fraction Debt Securities Mature $<$ 1yr). This latter finding makes sense given that, all else equal, maturing securities will disappear from the balance sheet and would therefore look like a sale from our perspective.

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; $\Delta$ FFP / Assets; $\Delta$ 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). 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.

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

**Figure B.5.** Variable Importance Across Models: All Variables

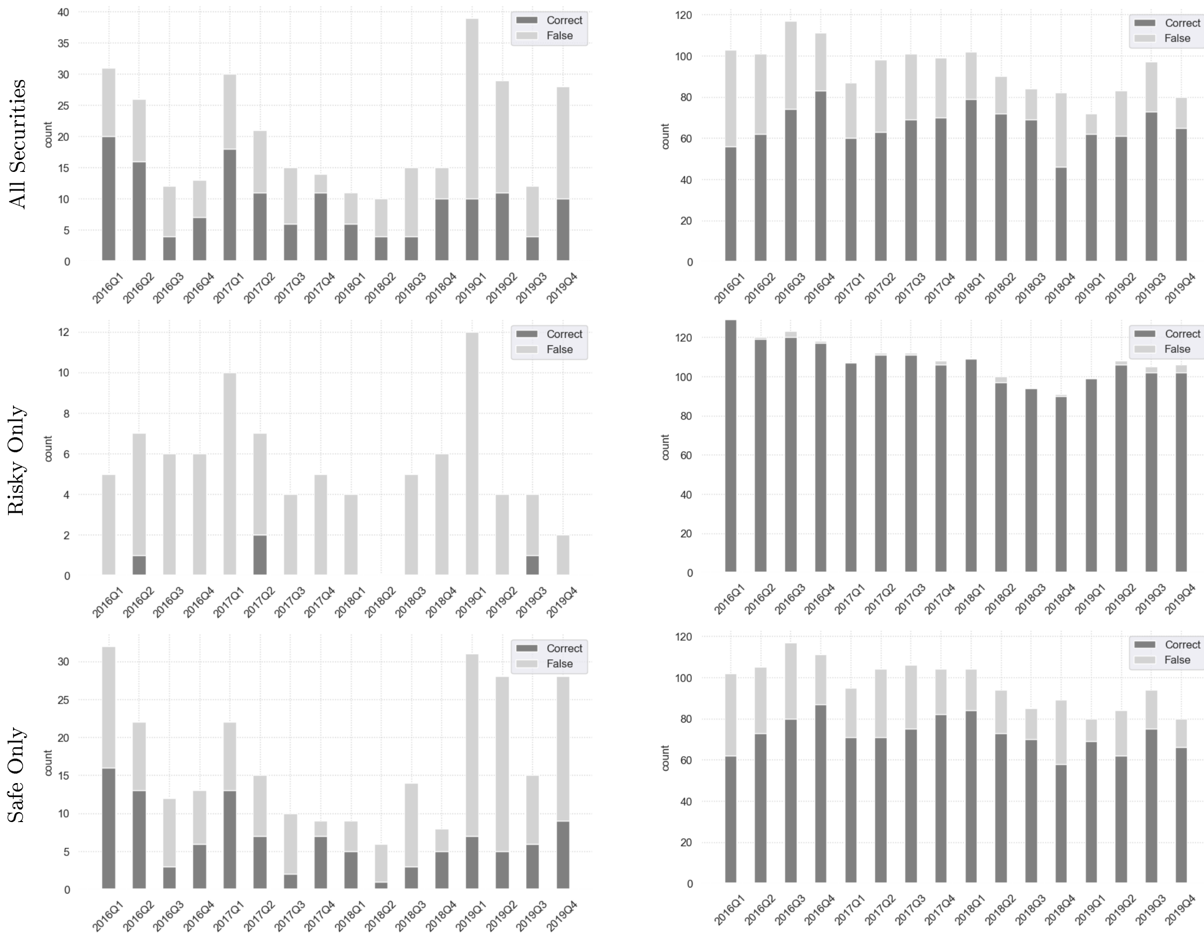
The overall importance ranks of the BHC characteristics are constructed as the sum of their importance rank from all models, measuring their overall contribution to predicting bank selling activities. The color gradients within columns indicate the model-specific variable importance of the characteristics. 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

**Figure B.6.** 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

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 B.6 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 B.6 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.