Does relative valuation work for banks?

ABSTRACT

We study the distribution and properties of valuation errors yielded by banking industry multiples for European and U.S. banks. The results highlight that stock-market multiples are best suited for U.S. institutions, and that a two-year-forward P/E is the most precise metric. Contrary to practitioner beliefs, P/tangible book value is less meaningful than P/BV. Multiples are less accurate for small commercial banks than for large ones, and for investment banks than for retail banks. We investigate whether large positive errors lead to one-year positive price performances and negative errors to negative price changes, and find that the forward P/E loses its predictive ability in comparison with historical multiples. Testing three investment strategies, we find that bank multiples can be profitably used in portfolio choices.

JEL classifications:

G11

G21

G32

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1. Introduction

Researchers in finance and accounting have extensively debated how well stock-market multiples work for equity valuation of nonfinancial companies (e.g., Alford, 1992; An, Bhojraj, & Ng, 2010; Bhattacharya, Black, Christensen, & Larsson, 2003; Bhojraj & Lee, 2002; Bhojraj, Lee, & Oler, 2003; Cheng & McNamara, 2000; Kim & Ritter, 1999; Lie & Lie, 2002; Liu, Nissim, & Thomas, 2002, 2007; Schreiner, 2007; Yee, 2004), but there is less research and evidence on the equity valuation of banks and other financial institutions. The relative valuation approach may represent the simplest way to value a bank: it determines the equity value of the bank as a function of selected fundamentals and the mean price of peer banks (Nissim, 2013). Analysts' opinions based on this approach are found everywhere in business and equity research reports.[1]

Despite the wide use of stock-market multiples among practitioners, research on their application in the banking industry is noticeably lacking. We do not know very much about the relative valuation performance of banking multiples and their role in sorting profitable investment strategies. As Flannery, Kwan, and Nimalendran (2004) have pointed out, banks are intrinsically difficult for outsiders to value because they are informationally opaque. We reckon that this reason alone warrants a special investigation into the banking industry.

This paper analyzes the valuation accuracy of multiples for U.S. and euro area banks. We first measure the performance of multiples based on equity book value, revenues, trailing

[1] Asquith, Mikhail, and Au (2005), analyzing a sample of 1,126 analyst reports delivered from 1997 to1999, show that 99.1% of equity analysts state in their reports that they employ multiple metrics, but only 12.8% mention using any alternative to discounted cash flow valuation. Few analysts use other valuation approaches. All analysts who cite a valuation method employ an earnings multiple.

earnings, forward earnings, common dividends, total dividends, tangible book value of equity, bank deposits, and customer deposits. In order to do so we develop a thorough method in which valuation errors are measured by how closely the valuation yielded by a given multiple approximates the firm's equity market price.

In the second part of the paper we explore whether an investment strategy based on the precision of industry multiples can be profitable over time. In particular, we examine the relationship between large valuation errors and subsequent stock returns. The destabilizing effects of bank opacity on bank stock price efficiency (Blau, Brough, & Griffith, 2017) offer a good reason for studying this relationship. More specifically, we assess whether large positive errors lead to systematic one-year positive price performances and whether negative errors lead to negative price changes.

In section 2 we describe banks' relative valuation, introducing all the multiples we analyze. In section 3, a review of the literature highlights the main findings of previous studies and fields where empirical evidence is still absent. Section 4 describes our data and methods and presents the results for each subsample; this section also examines the impact of the 2007–2009 financial crisis on the accuracy of relative valuation. In Section 5 we report a correlation analysis investigating whether significant positive and negative valuation errors, corresponding to potentially undervalued and overvalued banks, are reflected in subsequent price reactions. The final part of the section deals with the performances of long, long-short, and market-adjusted investment strategies, using the valuation errors computed in the previous section to assess whether stock selection strategies based on multiples' accuracy can be profitable. Section 6 summarizes our conclusions.

2. Relative valuation in the banking industry

2.1. Multiples valuation assumptions

The logic of relative valuation postulates that equity market prices are efficient and the law of one price holds, so that comparable firms are traded at equivalent prices (Fama, 1991). Additionally, value should be proportionally linked to the value driver, and this relation must hold for the entire peer group of comparable firms. Finally, prices are thought to be close to the fundamental value (Nissim, 2013), although this relationship sometimes varies because of speculation or significant price fluctuations.

Relative valuation metrics have certain drawbacks. First, relative valuation does not permit jointly investigating more than a single value driver. The selection of the denominator, the fundamental value driver, may give rise to biases: different value drivers can entail different conclusions (e.g., the overvaluation or undervaluation of a given company), and practitioners can select those that a priori best match their goals. Also, multiples are based on an assessment at one point in time and assume no significant change in the firm's business, competition, and market share (Schreiner, 2007). Furthermore, the approach is circular: the relative valuation of Bank A must address comparable firms such as Bank B and Bank C; however, the valuation of Bank B embraces Bank A and Bank C, and that of Bank C considers Bank A and Bank B. Hence, multiples should be used with judgment and value estimates should be corroborated, where possible, by adopting other valuation techniques such as traditional discounted cash flows analysis.

2.2. Bank opaqueness, stock price efficiency, and bank valuation

A major concern discussed in the financial literature that is particularly relevant for our research is bank opacity: are bank assets more opaque than those of similar-sized nonbanking firms? As the theory of efficient markets posits that asset prices reflect all publicly available information (Fama, 1991; Fama & French, 1992), what happens if information about risks associated with the bank assets is relatively opaque?

Several studies in the financial literature have dealt with this topic indicating that opacity in the intermediation process provides uncertainty to investors about the inherent risks of banks. Under these conditions bank stocks become hard-to-value assets.

Morgan (2002) finds that bond ratings for banks are much more dispersed than for other firms, as agencies have more difficulty in assessing the risks. In contrast, Flannery et al. (2004), using stock-market microstructure features such as bid-ask spread, trading activity, and return volatility, provide evidence that bank stocks are not more opaque than those of nonfinancial firms trading in the same market (either NASDAQ or NYSE/AMEX). Additionally they show that, on average, I/B/E/S research equity analysts predict bank earnings rather accurately, with forecast errors statistically similar to those for nonbank firms. In 2013, the same authors updated their research on the U.S. markets in order to consider the 2007–2009 financial crisis, and found that during "crisis" times the relative opacity of banks indeed increases, consistently with the presumption that a fall in a bank's asset values will increase the opacity of its equity. These results are strongly supported by other studies (Blau et al., 2017; Huizinga & Laeven, 2012; Jones, Lee, & Yeager, 2012). Blau and colleagues (2017) indicate that stock prices of banks are less efficient than those of nonbanks, especially during crises. Importantly, they show that the relative inefficiency still persists during noncrisis periods. They conclude that bank opacity results in greater exposure to contagion and higher systemic risk, impeding the efficient transmission of information into stock prices.

Major findings of this strand of literature on the banking industry suggest the following valuable insights:

- equity research analysts are able on average to provide bank earnings forecasts that are no less accurate than those performed for other industries in "normal" periods of economic and financial activity;
- bank opacity increases and becomes a more acute issue during "crises";

- stock price inefficiency due to opacity is higher for banks than for other stocks.

These insights have implications for a study of banking multiples' accuracy. First, bank multiples that rely on I/B/E/S consensus earnings forecasts should still retain informational value. Second, as bank opacity is higher during "crises," we should analyze the performance of bank multiple separately for normal and crisis times. Third, the relative inefficiency of bank stock prices implies a greater probability of mispricing of bank stocks.

Potential bank stock mispricing brings two consequences for our research focus. On one hand, it makes valuing banks through multiples tricky, as observed market prices are not a reliable measure of the equity value. In this case the "valuation error"—the distance between the equity value estimated through a banking multiple and the observed market price—is biased, as the market price is not fully efficient. This requires additional caution in interpreting the results of our analyses of multiples' accuracy.

On the other hand, potential mispricing heightens the motivation for exploring whether an investment strategy based on multiples' precision, as the screening factor, can provide profitable returns, since alpha seeking portfolio strategies based on stock return predictability are more common in inefficient markets (McLean & Pontiff, 2016).

2.3. Banking multiples

Multiple metrics can be formed from countless operative, accounting, financial, or capital quantities. The most popular are revenues, EBITDA, EBIT, earnings, and book value of equity. Below we focus only on the measures most commonly used by analysts and practitioners in the banking industry.[2]

2.3.1. Price/ equity book value

[2] Multiples that employ EBIT and/or EBITDA as value drivers are used mainly for nonfinancial corporations, so they are not considered in this paper.

This ratio is broadly employed for capital-intensive businesses, although it is less important for industries where the key fundamental of equity value is prospective growth, such as technology or new social media. The measure is suitable for financial institutions because of the regulatory stress on solvency, capital requirements, and equity maintenance. However, equity book value does not capture relationships between assets and fee-generating activities, which are typical in banking.

2.3.2. Price/tangible book value of equity

In this ratio the value of all intangibles is subtracted from equity. According to many scholars and practitioners the most important intangibles for banks are goodwill, core deposit intangibles, mortgage servicing rights, present value of future profits, purchased credit card relationships, and customer relationships.

2.3.3. Price/revenue

Despite its simplicity, this multiple is infrequently used and often criticized. Sales should be compared only with asset-side items (e.g., enterprise value) and not with equity measures. Moreover, comparing firms on this basis does not consider firm cost structure and may therefore lead to misjudgments.

2.3.4. Price/earnings

This is the most popular metric for relative valuation. It is computed as the stock price divided by earnings per share (EPS) (or total equity market value above net income). Practitioners rely on different versions according to the definition of net earnings. First, the multiple can be trailing or forward. Trailing multiples take reported values: for example, the net income of the last twelve months (LTM). Forward multiples employ analysts' consensus forecasts for earnings. Analysts can project one-year or multiple-year estimates. One- or two-year-ahead forecasts are more commonly used. Yee (2004) showed from a theoretical perspective that forward earnings are regularly a more accurate value driver, and the farther ahead, the more precise. Second, in measuring EPS, one can count outstanding common shares (basic P/E) or diluted common shares (diluted P/E). Dilution posits the exercise of all outstanding convertible securities (convertible bonds, warrants, and stock options), thus increasing the total number of shares outstanding, and triggering a cut in EPS and an increase in the ratio. Lastly, net income may include or exclude specific nonrecurring items. The rationale for excluding them is that unusual and infrequent gains or losses should be irrelevant in valuation because they do not affect future profitability. We examine the following P/E specifications:

- P/one-year-forward earnings
- P/two-year-forward earnings
- P/LTM diluted earnings, considering extraordinary items
- P/LTM diluted earnings, excluding extraordinary items
- P/LTM basic earnings, considering extraordinary items
- P/LTM basic earnings, excluding extraordinary items

For loss firms, the P/E ratio becomes meaningless as the denominator assumes negative values. For firms with low earnings, we often have to deal with outliers that inflate the ratio. For banks that report large provisions for credit losses, the ratio becomes more volatile. Also, as earnings represent the bottom line of the income statement, they can be influenced by various accounting strategies.

2.3.5. Price/dividends

For this ratio, share price is divided by dividend per share or, equivalently, market capitalization is divided by total dividends. Dividends are typically distributed more than once a year (usually quarterly), and these cash flows must be summed to obtain a yearly value. This multiple could be applied to every firm in the market, but would be meaningless in the case of companies that do not distribute dividends because they prefer other types of shareholder remuneration (such as share repurchase programs), or because they want to invest internally in order to grow. However, this multiple is often used in banking because dividends represent the only meaningful cash flow and because intrinsic valuation using dividends still occurs.

The denominator may consider only common dividends, or total dividends, the sum of common and preferred dividends. Both forms of this multiple are particularly affected by outliers. If dividends are low, the multiple may skyrocket and compromise valuation.

2.3.6. Price/deposits

Deposits distinguish banks from nonfinancial businesses. Deposits are crucial for retail banks; therefore, they are appropriate for providing an operating multiple in the banking sector. We use two versions: one counting only deposits from other banks (that is, representing involvement in the interbank market), and the other counting only customer deposits (savings and time deposits held on account for households, partnerships, and corporations).

3. Literature review

Nissim (2013) analyzed the accuracy of relative valuation for 372 U.S. insurance firms, using monthly data from March 1990 to January 2011. His results showed that valuation based on analysts' earnings forecasts betters valuation performed on historical earnings, evidence confirmed by our work. Nissim also proved that book value multiples perform robustly, particularly when the price-to-book ratio is conditioned to return on equity (ROE). The author emphasized that diluted shares are more predictive than outstanding common shares, and earnings before special items are more predictive than reported net earnings. In a previous paper, Liu, Thomas, and Nissim (2002) presented a broad investigation of multiples' precision in the U.S. market between 1982 and 1999 and obtained a ranking that is consistent in almost every industry they analyzed (mainly nonfinancial industries). They found that forward earnings measures are superior, followed, in order, by historical earnings measures; cash flow measures, together with book value measures; and sales measures.

Apart from Nissim's work on the insurance industry, most of the existing studies focus mainly on nonfinancial firms, though in some cases they may be relevant also for banks. Cooper and Cordeiro (2008), for example, discussed the optimal number of comparable firms to be used when computing out-of-sample multiples. The authors provided evidence that five comparables can be enough when the comparable firms are selected from the same industry, have approximately the same expected growth rates, and have an average growth rate within 1% of the target firm's growth rate. Increasing the number of comparable firms brings more information but also more noise.

Cheng and McNamara (2000) explored the precision of trailing P/E and P/BV multiples, and an equally weighted combination of the two, in nonfinancial sectors. In the U.S. equity market (first considered as a whole and then divided according to SIC codes), the combined P/E-P/BV multiple performed better than either P/E or P/BV alone, which suggests that both earnings and book value fundamentals are relevant to value.

Alford (1992) explored how alternative methods of identifying comparable firms and metrics for growth and risk affect the accuracy of valuations using earnings multiples. He found that valuation precision improves once the industry code for comparable firms is specified at the three-digit SIC level. Bhojraj and Lee (2002) studied matching comparable firms on underlying fundamental variables rather than industry and size. They showed that comparable firms selected on the basis of profitability, growth and risk characteristics offer sharp improvements over other approaches of comparable firm selection.

Lie and Lie (2002) found that book value multiples deliver more accurate estimations than revenues and earnings multiples, and that the precision and bias of the estimated values fluctuate significantly by firm size, profitability, and the presence and extent of intangibles. Park and Lee (2003), in an analogous investigation on the Japanese stock market, found that P/BV is more predictive than ratios using earnings, EBIT, revenues, and cash flow.

More recently, Penman and Reggiani (2013) linked P/E and P/BV in a two-step approach. First they ordered P/E by deciles and then, within each P/E decile, they sorted by P/BV. In debating the "value effect" discussed by asset pricing theory, they underscore that investors in value stocks—that is, stocks with lower than average multiples—may be caught up in purchasing stocks with expected earnings growth that could end up to be rather risky. They explain the value "premium" as a risk premium, albeit through a quite different interpretation from that offered by the classical asset pricing theory assuming an efficient market (Fama & French, 1992, 2012). Unluckily they analyze only nonfinancial firms.

More limited analysis has been conducted on the performance of multiples in the European context. One exception is Herrmann and Richter's (2003) study of nonfinancial firms. They showed that metrics centered on earnings are most accurate and those built on sales the least reliable, and that the P/BV multiple is superior to the asset side EV/EBITDA multiple once comparable firms are chosen according to ROE and earnings growth instead of industry groupings alone.

Schreiner (2007), also looking at European markets, found that equity value multiples outshine asset side multiples. He verified a finding common to many other studies: regardless of the sector, forward-looking multiples always produce more accurate valuations than trailing multiples. Less predictably, cash flow ratios (such as price to dividends and price to operating cash flows) are better than book value multiples (price to book value and price to total assets).

In sum, to the best of our understanding, there is little empirical research focusing exclusively on the banking industry; and considering banks' peculiarities, the presumed opaqueness of their assets, and the tailor-made multiples used in valuing them, such research need not be limited to the approaches used in assessing nonfinancial industries. Also, as European and U.S. financial institutions are subject to quite different regulations and supervision, we reckon that it is key to include firms in both markets.

4. Performance and accuracy of banking multiples

4.1. Sample and data

Our large and unique database includes all U.S. and euro area banks with data simultaneously available in Compustat, Bloomberg, and the Institutional Brokers' Estimate System (I/B/E/S). We detect banks using the Global Industry Classification system (GICS) industry code 4010, and we include even delisted banks that were listed for a certain period within our time horizon, in order to avoid survivorship bias in the dataset. Delisting can be explained by M&A activity (in most cases), by strategic management decisions (in rare cases), or by bankruptcy. The database includes 950 listed and delisted financial institutions: 172 European (of which 41 have been delisted) and 778 U.S. (of which 275 have been delisted). Our European banks include listed banks from the following 16 euro area countries: Germany, France, Italy, Spain, Netherlands, Belgium, Portugal, Ireland, Austria, Slovakia, Finland, Slovenia, Greece, Luxembourg, Cyprus, and Malta. We consider only euro area banks in order to limit concerns about the actual comparability of price multiples due to differences between countries and country risks.[3] U.S. banks are banks listed on the main U.S.

[3]In the eurozone countries, the economic and financial integration warranted by the introduction of a single currency has smoothed out country differences over time. Moreover, banks from peripheral eurozone countries that are deemed more risky, such as Greece, Cyprus, and Malta, present a quite low proportion in our sample (see Table 1, panel A).

stock exchanges (NYSE and AMEX). Table 1, panel A presents more details on the sample composition.

[insert Table 1 about here]

The time span for our study starts from year 1990 and ends with 2012. We have not extended our analysis beyond 2012 for the following reasons. First, we need to exclude the years affected by the euro area sovereign debt crisis. A comparison between U.S. banks and euro area banks after 2012 would be severely biased, since euro area banks have been heavily affected by the Greek sovereign debt crisis while U.S. banks have been substantially untouched.[4] Second, we are particularly interested in the behavior of banking multiples during the 2007–2009 subprime crisis, which was a truly global financial shock. Still, our time horizon is long enough (23 years) to capture the evolution of the multiples' accuracy through diverse economic and stock-market cycles.

All the historical balance sheet and income statement data are taken from Compustat, along with the number of shares outstanding. Compustat does not provide the amount of bank

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Nevertheless we repeated our analysis on different country subsamples (such as core eurozone countries versus peripheral countries) and found no significantly different results.

[4] Another significant problem regarding the years soon after 2012 concerns the very heterogeneous impact of the sovereign debt crisis on euro area banks across different countries (especially Germany, France, the Netherlands, and Belgium versus distressed southern European countries). Hugely different country and sovereign risks (exposed, for example, by the escalating credit spreads on government bonds in the distressed euro area countries) have markedly differentiated the value of multiples of banks in different countries. For this reason the aggregate European sample results would be highly biased by the countries included in the sample.

deposits for U.S. banks, and the corresponding multiple cannot be computed. Moreover, it does not distinguish between diluted and basic P/E for European banks, which causes missing data in two multiples: P/LTM diluted earnings considering extraordinary items, and P/LTM diluted earnings excluding extraordinary items.

Prices are taken from Bloomberg. To compute multiples we normally select the end-of-April price, following the standard practice in the literature and Nissim's (2013) study on relative valuation performance in the insurance sector. Selecting prices four months after the fiscal year end guarantees that all year-end information is publicly available and discounted in prices.[5] We take analysts' forecasts from the Institutional Brokers' Estimate System (I/B/E/S) database in order to compute forward metrics.

The heterogeneity of the sample, along with the need to keep European and U.S. firms separate, requires that we divide banks into two subsamples: investment and commercial, or retail, banks. Following Beltratti and Stulz (2012), we base the classification on a summary ratio, gross loans/total assets, with a threshold of 40%: banks exceeding the limit are considered commercial/retail banks.[6] The summary ratio is computed as the median of the annual gross loans/total assets ratios available between 1990 and 2012. We then group commercial banks (which are much more numerous) as small and large: large banks are those that exceed the median of total assets per bank during the timespan. These data are summarized in Table 1, panel B. In robustness tests we have used different cut-off points for total assets (such as the US$50 billion used in the Dodd-Frank U.S. regulation), but our main results do not change significantly (evidence not reported here).

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[5] Moreover, the Institutional Brokers' Estimate System (I/B/E/S) updates and publishes summary forecasts in April, increasing consistency between prices and analysts' forecasts.

[6] Gross loans data for our sample are taken from the Bankscope database.

Size affects bank value. Large banks are less risky because their international reach provides broader access to customers and depositors, enhancing recurring revenue. Moreover, large banks can be perceived to be too big to fail or even too systemic to fail,[7] and they have superior market power, enjoy economies of scale or scope, and benefit from increased diversification, all of which offer potential cost savings. Large banks may be more financially flexible than smaller banks because they have easier access to capital market funds (Calomiris & Nissim, 2007). In contrast, small banks often operate as niche players on a regional basis. Presuming sound financial conditions and adequate financing capabilities, small financial institutions have greater strategic flexibility and growth potential.

Appendix 1 summarizes the medians of the banking multiples across all sampling years, and also displays the first quartile, the third quartile, and the 95th percentile. These summary indicators offer a quick overview of multiples' values in the banking industry, distinguishing between European and U.S. firms, retail and investment banks, and large and

[7] The financial crisis, which began in 2007 in the United States, and the Lehman Brothers insolvency the following year demonstrated that the collapse of an interconnected bank can jeopardize the stability of the global financial system and have severe implications for the real economy. Since 2009, supervision authorities such as the Financial Stability Board and Basel Committee on Bank Supervision have promoted regulatory changes in order to reinforce the stability of the financial system and new rules designed to address the too-big-to-fail issue, as is implied by the publication of a list of systemically important financial institutions (SIFI) and new capital requirements for them. The first list of 29 SIFIs was disclosed by the FSB and the BCBS on November 4, 2011. For a review on this topic see Bongini, Nieri and Pelagatti (2015).

small retail institutions. The summary also clarifies that multiples are skewed to the right once they are centered on reported fundamentals and not on analysts' predictions.

4.2. Methods

We compute multiples for each bank in each year. Relative valuation is founded on out-of-sample multiples (that is, the bank being valued is omitted from the peer group of banks included in calculating the multiple). Practitioners and scholars deem this approach the most consistent because it curtails potential biases. To limit the effect of outliers, in calculating multiples we use the harmonic mean,[8] which is the preferred method used in previous studies (Liu et al., 2002; Nissim, 2013).[9] To estimate the fundamental value, we multiply the out-of-sample harmonic mean peer group multiple by the corresponding value driver. The harmonic

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[8] The harmonic mean averages the inverse of the multiples. The arithmetic mean is affected largely by banks that exhibit unusually high multiples, due, for example, to temporarily depressed earnings in the case of the P/E metric. The harmonic mean is not skewed as much by such firms. Since the arithmetic mean is always higher than the harmonic mean, employing the former will always overestimate value. The harmonic mean H can be computed by dividing the number of bank multiples, n, by the sum of the inverses of the banking multiples, $x_1, x_2, \ldots, x_n$:

$$H = \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \cdots + \frac{1}{x_n}}$$

[9] We tested our results using the simple mean instead of the harmonic mean and removing observations (winsorizing) at the top and bottom 1% and 5% of their distributions, within each multiple metric and subsample. The results did not alter significantly.

mean peer group multiple is computed considering all firms belonging to the same regional market and size-business group as the bank under valuation.

If market prices are efficient, a fundamental value close to the current market price indicates that the multiple used performs well. Valuation error is calculated by subtracting the current market price from the fundamental value and dividing this difference by the current price, so that diversities in scale among prices have no misleading effects. Dittmann and Maug (2008) determined that this method for computing errors yields the least biased error when the harmonic mean aggregates the multiples of comparable firms, as is the case here.

Where x is the bank valued and t is the designated year, we define the formula for the valuation error as follows:

$$Valuation\ Error\ (x\ ;\ t) =$$

$$= \frac{Peer\ group\ multiple\ (all\ banks\ except\ x\ ;\ t) * Value\ Driver\ (x\ ; t) - Market\ Price\ (x\ ; t)}{Market\ Price\ (x\ ; t)} \quad (1)$$

This definition represents the core of our analyses. Using it we perform a first assessment that basically replicates Cooper and Corriero's (2008) procedures, employed also by Rossi and Forte (2016): in order to appraise the accuracy of alternative multiples, we compute the bias, the mean absolute deviation (MAD), and the mean-squared error (MSE) of the valuation errors. Formulas used are the following:

$$Bias = \frac{1}{T} \sum_{t=1}^{n} \sum_{x=1}^{X} Valuation\ Error\ (x\ ; t) \quad (2)$$

$$MAD = \frac{1}{T} \sum_{t=1}^{n} \sum_{x=1}^{X} |Valuation\ Error\ (x\ ; t)| \quad (3)$$

$$MSE = \frac{1}{T} \sum_{t=1}^{n} \sum_{x=1}^{X} Valuation\ Error\ (x\ ; t)^2 \quad (4)$$

where T specifies the aggregate observations (each bank for each year) and X represents the number of banks in the peer group (subsample).[10]

The results are shown in Appendix 2. The MSE is estimated employing a 95% winsorization because errors are squared when computing MSE and large positive outliers may harm the outcomes.[11] Appendix 3 shows the distribution of valuation errors, highlighting the bias, 5th percentile, first quartile, median, third quartile, and 95th percentile.

In order to better appraise the accuracy of alternative multiples' metrics we assess the distance between the fundamental valuations and the actual prices. For each metric we compute the percentage of banks that display observations whose calculated fundamental value lies within 10%, 25%, 50%, 75%, and 90% of the actual market price. Table 2 describes these statistics. Higher percentages of banks falling within the 10% and 25% ranges underline stronger relative valuation accuracy of the multiple being used.

[insert Table 2 about here]

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[10] Applying diverse accuracy measures yields a more balanced appraisal of the multiples' performances. Bias alone could be deceptive owing to the possibly counterbalancing effects among positive errors and large negative errors. The MAD and MSE measures address this issue by taking into account only errors with positive signs; moreover, MSE imposes a stronger penalty for large errors and is often preferred theoretically although its accuracy declines when outliers are present.

[11] Winsorization replaces values exceeding a given threshold (in our case, the 95th percentile) with the threshold value itself. This technique is preferable to simple trimming since no observations are dropped and the original sample size is preserved. This practice is standard and is adopted, for example, by Beltratti and Stulz (2012) in their analysis of the impact of governance and regulation on banks' performance during the credit crisis.

It is worth highlighting that the values obtained in our analysis are consistent with the findings obtained by Nissim (2013) for multiples used by insurance companies. This similarity might be explained by banks' and insurance companies' similar business structures and value drivers.

4.3 Results

We summarize here the evidence on multiples' accuracy, discussing both the findings that are consistent across all subsamples and the specific evidence associated with each subsample. Multiples for U.S. banks are more accurate than multiples for European banks across every subsample (investment banks, commercial banks, and small and large retail banks). Thus valuation by means of multiples will be more troublesome for European banks.

Large commercial banks display the most accurate multiples, both in Europe and in the United States. For the United States, the banks with the least accurate multiples are investment banks. The particular business model and functions of these banks imply that every institution should be modeled separately, and that comparability is often problematic. In Europe, the evidence is more intricate. Although investment banks demonstrate the lowest performance by forward P/E multiples, they get better performance than small commercial banks do from all other multiples except P/customer deposits, which is best suited for retail banks.

Forward P/E metrics are better value indicators than trailing P/Es—quite predictably, as price discounts expected earnings. Compared to reported earnings, analysts' earnings forecasts provide a more direct estimation of prospective profitability and, because they reflect a larger information set, are likely to be more precise (Nissim, 2013). Moreover, I/B/E/S analysts' estimates dismiss the effect of unexpected transitory shocks to recurring items (such as unexpected revenue from an unusually large transaction) in addition to "one-time" items (for example, realized gains and losses), thereby obtaining a better proxy for core earnings that should persist in the future.

Multiples including two-year earnings forecasts are more accurate than multiples that use one-year estimates. This finding is consistent with the theoretical hypothesis of Yee (2004). In Europe, the historical P/E that includes extraordinary activity performs slightly better, but the differences are not significant. In the United States, the discrepancies are even more subtle, but the results suggest that the best metric is a multiple based on diluted EPS excluding extraordinary items, which should lessen the instability of book value and alleviate accounting biases.

It is a common belief among analysts and equity research teams that the P/BV multiple is a biased metric for the banking industry, and that it is necessary to correct it by subtracting intangibles from the book value of equity. Our research demonstrates that this belief is unfounded. P/BV consistently shows smaller valuation errors than P/TBV. A unique exception to this finding is the subsample of European investment banks. At a 10% accuracy level, P/BV captures 10.8% of these firms, whereas P/TBV obtains 12.3%. However, if the precision bound is relaxed to 25% or more, the P/BV multiple becomes more accurate than P/TBV.

It is evident that P/common dividends is more suitable than P/total dividends for European banks. Preferred dividends can be compared to extraordinary items and should be excluded from estimations. The difference between the two multiples is not relevant for U.S. commercial banks, where the two multiples perform about equally well.

Compustat lists both bank and customer deposits for European banks. The first type of deposit is more important for investment banks, which rely on the interbank market rather than individual and corporate deposits, whereas the opposite is true for retail banks.

Accordingly, we find convincing evidence that the bank deposit multiple is best suited for investment banks whereas the customer deposit one performs better for retail banks.

For small retail banks in the European sample, historical P/Es and price to book value metrics provide very weak performances. Still, forward P/Es perform much better for small retail banks than for investment banks. Our results seem to indicate that equity analysts should look only at forward P/Es when assessing European small retail banks.

For equity research analysts, investment bankers, and portfolio managers, the evidence discussed here can help identify those regional markets and business-size segments in the banking industry in which valuation errors turn out to be bigger and more unstable, so that banking multiple metrics do not work very well in explaining current market prices.

4.4. Performance across time

Our data can be used to explore the evolution of multiples' accuracy from year to year, focusing on the percentage of errors that deviate by less than 25% from the current market price. European data are limited, or even missing, for the first half of the 1990s, particularly for investment banks. The same is true for U.S. investment banks. Thus we cannot analyze all our subsamples across time.

Figure 1 shows that for large European commercial banks, volatility and randomness among years are significant. Some conclusions can be drawn, however, particularly if the starting point is postponed to 1998.

[insert Figure 1 about here]

Multiples valuation (particularly using the forward P/E multiples) is severely affected at the start of the subprime financial crisis, but there is an upward swing in the last two years. Relative valuation accuracy also worsens because of the internet firms bubble burst owing to weak links between prices and fundamentals.

Stronger insights emerge in the analysis of U.S. retail banks (Figure 2).

[insert Figure 2 about here]

The performances of forward and historical P/Es, P/revenue, P/BV, and P/customer deposits are correlated. Multiples in general perform poorly after the year 2000, reflecting the impacts on banks of the dot-com bubble collapse. Relative valuation also suffers a substantial decrease in accuracy in 2008 and 2009. In the years soon after the subprime mortgage crisis, forward multiples progressively lose their ability to outperform most trailing/historical multiples (especially trailing P/E and P/BV).

Similar findings can be observed in the sample of U.S. small commercial banks shown in Figure 3. The internet bubble crash impairs the precision of multiples as in the sample of large retail banks. During the subprime crisis and the ensuing financial crisis, both forward and trailing P/E accuracy performances recover more slowly than in large retail banks.

[insert Figure 3 about here]

4.5. The effect of the subprime financial crisis on banking multiples' accuracy

Many studies in the finance literature have discussed the effect of the U.S. mortgage crisis on the banking industry. Huizinga and Laeven (2012), for example, report large differences between market and book value of the assets of banks. By the end of 2008, 60% of U.S. banks exhibited a market to book ratio of assets below one, compared with only 8% of banks at the end of 2001. Distressed, hard-to-value assets like mortgage-backed securities registered a sharp drop in value due to information asymmetries about their quality. For these reasons we can expect, as we have already seen, that the crisis had a noteworthy impact on multiples' accuracy. Table 3 compares the yearly average percentages of valuations that lie within different ranges of the actual market price before and after the crisis (1990–2007 and 2008–2012).

[insert Table 3 about here]

The last columns of the table show the difference between precrisis averages and crisis-years values (negative values indicate multiples that were performing better before the financial crisis). The accuracy of forward P/Es, especially for valuations within 10% and 25% of actual price, drops very substantially and much more than that of the other historical multiples. Forward P/E (FY2), the two-year-ahead forecast, tends to decline more. The only exception is the subsample of European investment banks, which shows a slight improvement. The decline is less severe for small retail banks in Europe, while for U.S. banks there is substantial uniformity among large and small firms.

Trailing multiples present a more mixed picture. In the small retail segment both U.S. and European banks show a generalized decline in accuracy for all multiples except the trailing P/Es, which exhibit a moderate increase. For large commercial banks all the trailing multiples show good resilience, especially in Europe, where P/bank deposits multiples perform best. In the United States we have a more mixed situation. Among European firms, trailing multiples appear to be less affected by the financial crisis in the investment banks segment.

In general, multiples—especially forward ones—rapidly lose predictive accuracy throughout phases of uncertainty triggered by financial crises. Under these circumstances practitioners should select alternative valuation models such as discounted cash flow analysis and similar conventional absolute valuation approaches. Our results tend also to corroborate the main findings in the literature on bank opacity (see section 2.2), which show that during crises increased bank opacity turns bank equity into a hard-to-value asset.

5. Are bank multiples effective for choosing investments?

Can multiples be used as an investment tool? In this section we examine whether large valuation errors (both positive and negative) are related to subsequent stock returns. Here we implicitly abandon the assumption of market efficiency and posit that market prices can deviate from intrinsic values, as they do not correctly reflect the fundamentals we investigate. The effect of bank opacity on stock price efficiency and bank valuation, discussed in section 2.2 and demonstrated by robust empirical evidence (Blau et al., 2017; Jones et al., 2012), gives us good reason to explore this question.

Moreover, a recent study on stock return predictability (McLean & Pontiff, 2016, p. 21) shows that among 97 variables that have been empirically shown to predict cross-sectional stock returns, multiples ratios display smaller declines in out-of-sample and post-publication tests than do event, market, or fundamentals predictors. This research indicates that investors usually learn about mispricing from academic studies, while the valuation predictors exhibit a stronger predictive ability over time even in the out-of-sample tests.

5.1. Method

The following analysis relies on the same database used above, with two adjustments. First, European banks are entirely excluded, for three main reasons:

- our data on European banks present a shorter time series than the U.S. data;[12]
- the European banks sample is much smaller than the U.S. sample (172 versus 778 firms);
- as banking multiples are more accurate for U.S. banks (see section 4.3), it makes more sense to test stock selection strategies using multiples' accuracy as a screening factor in the U.S. market, where it should be more difficult to exploit potential mispricing.

[12] We need the longest available data series because in section 5.3 we sort buy-and-hold portfolios on valuation errors rankings measured once a year at the end of April.

Second, we do not examine subsamples but instead lump together investment banks and large and small retail banks, using the valuation error distributions arising from the previous analysis as the key input in this second step of our study.

The aim is to test whether banks with large valuation errors present systematic price movements in the following year. Every year, for each multiple, we select two groups of banks, those that rank in the top and bottom deciles of the errors distribution (i.e., the tails of the distribution). By our definition of errors (see Equation 1 in section 4.2), substantial positive errors correspond to potentially[13] undervalued financial firms, while the negative tail of errors should identify overvalued banks. The prices of these extreme valuations should converge to intrinsic, fundamental values (those implied by the multiples), and we investigate whether this occurs. The procedure is repeated for each year for all banks in both tails and for each multiple. Depending on the purpose of the subsequent analyses, we have considered both raw (absolute) returns and market-adjusted returns. In the latter case, to isolate price changes that are due specifically to bank-related issues, we subtract the systemic/market portion (proxied by returns on the S&P 500 index) from the raw return.[14]

We extend the analysis by combining two or more multiples, equally weighting their valuation errors and again identifying the top and bottom deciles of the distribution. Here we present only the results for the most relevant combinations. Combining alternative multiples is a convenient way to jointly take into account more than one value driver (Nissim, 2010), which should then strengthen the link with price movements.

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[13] We repeat: the valuation error depends on whether market prices efficiently discount all available information.

[14] Obviously, we compute the S&P 500 index returns at the end of April of each year to be consistent with the observations of banks' stock-market prices.

Once every observation belonging to the error tails is associated with the corresponding price change in the following year, we compute Pearson correlations between errors and subsequent price changes, for each year and multiple. Overvalued companies display negative errors and should have negative subsequent price performance, whereas undervalued banks show positive errors and should have positive price performance. Therefore, if extreme relative valuation errors capture some form of mispricing, correlations should always be positive.

5.2. Results

Table 4 shows the outputs of the Pearson correlation analysis for individual multiples; Table 5 shows the results for combinations of multiples.

[insert Tables 4 and 5 about here]

Each table is divided into two parts, panel A for the positive tail of undervalued banks and panel B for the negative tail of overvalued firms. One-year-later stock returns are always market adjusted. The last row of each table shows the number of positive and negative correlations for a given multiple throughout the years examined. Negative correlations, which discredit or at least limit the multiple's utility as a criterion for investing, are shown in italics.

Negative correlations are systematically more numerous in the left side of the distribution, the side with negative errors. Overvalued banks often remain overpriced—perhaps because we check equity returns only one year ahead, and because rumors of acquisitions or mergers can drive prices up for more than a year. Moreover, negative correlations tend to appear in the same years for all multiples: 1999 and 2004 for undervalued banks and 1994–1995 and 2000–2005 for overvalued banks. The negative correlations in 1999 may be attributable to the burst of the dot-com bubble in 2000, which affected the entire economy and drove all prices down. The 2000–2005 negative correlations can be intuitively explained by a euphoric and bullish stock market in the banking sector: even overvalued banks exhibited positive price performances, while undervalued ones showed quite frequent and significant positive correlations.

P/dividends and P/revenue should be avoided as investment tools because they have a weak bond with future price performance. Unexpectedly, forward P/Es should also be avoided. Although they may be the most precise metric for estimating the price of a bank, they cannot predict price changes for firms in the error tails. P/BV, P/TBV, P/deposits, and historical P/Es can predict future returns more accurately.[15]

[15] As a robustness test we perform a second type of analysis based on univariate regressions, where the dependent variable is price performance (returns), and the only explanatory variables are a constant term and valuation errors. Because only tails are considered, the number of observations is limited; to increase it and guarantee statistical significance, we combine all years. Positive and negative error tails are kept separate: for every multiple (or combination of multiples), two regressions are run. These regressions confirm that basing investments on the valuations yielded by forward P/Es might lead to weak results. With the exception of P/common dividends, there is no multiple that indicates a clear trading strategy for overvalued companies. However, there are some interesting indications for undervalued banks. Historical P/Es, together with P/customer deposits, should be the preferred metrics, whereas P/BV and P/TBV have coefficients significant only at the 12.5% and 15% levels, respectively.

Even the combinations of multiples appear to be weak tools when addressing overvalued banks. Surprisingly, the signs of the significant coefficients are negative, suggesting that banks that appear overvalued have a one-year positive (and not negative) price performance. The coefficient of the multiple composed of P/TBV and P/total dividends is not statistically different from zero, implying that this investment strategy does not permit

Table 5 presents results for eight combinations of multiples: seven that combine two different multiples, and one that aggregates P/BV, historical P/E, P/revenue, and P/customer deposits (equally weighted). These four multiples separately are probably the best predictors of future price performance, so a synthesis of them might be even better. We select P/E (basic, no extra) to represent the trailing P/Es. If we replace it with one of the other three versions of historical P/E, the results (not reported here) do not change significantly.

The correlation analysis displays immediate improvements, particularly when the trailing P/E is involved. The combination of the trailing P/E with P/TBV, P/customer deposits, or P/revenue can forecast a positive price performance for undervalued banks in 19 of the 22 years tested (Table 5, panel A). The synthetic multiple that combines four metrics ranks second best, though it does no better at predicting outcomes for the left tail of the error distribution. Another interesting result is that P/TBV combined with P/total dividends provides the most reliable indication for overvalued banks, performing better there than in the subsample of undervalued companies. The use of forward-looking P/Es is inefficient, even when they are combined with P/BV or P/TBV. Here we have a further confirmation that this version of P/E should be used to assess prices, but not to implement trading strategies.

The fact that forward P/Es best approximate stock prices but do not predict future price movements is not completely surprising. A large strand of literature on analysts' earnings forecasts, since the early 1990s, has proved that they do a poor job of explaining market price variation, especially over a one-year horizon (e.g., Abarbanell & Bushee, 1997; Bandyopadhyay, Brown, & Richardson, 1995; Das, Levine, & Sivaramakrishnan, 1998; for a

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systematic benefits from short positions in overvalued banks. The right tail of the regression distribution confirms that combinations including trailing P/E show a robust link between undervaluation and future price appreciation.

review of the literature see Ramnath, Rock, & Shane, 2008). Countless biases have been attributed to analysts—excess of optimism, underreaction, and herd behavior, to name a few. In addition, many other studies attest that historical earnings time series are very close to a random walk and feature mean reversion (for a review see Kothari, 2001). Considering that analysts have an obvious timing benefit from incorporating new information on price changes, dividends, and good or bad news, it is natural that their forecasts (forward P/E) will tend to closely mirror current market prices. This clearly implies greater accuracy in explaining current stock prices but less ability to capture misalignments with respect to past earnings trends, and therefore less ability to exploit mean reversion through stock picking. Gray and Vogel (2012) find results similar to ours.

5.3. Investment portfolio performance

Suppose that an investor wants to select a portfolio using the relative valuation errors analyzed thus far. Whereas our correlation analysis investigated the direction of future price movements for undervalued and overvalued banks, our portfolio analysis considers not only the sign of the price change for the subsequent year (t + 1) but also its amplitude. The correlation statistics reveal that the multiples with best valuation performance (P/E [FY2], [FY1]) are not as useful for investment decisions. The best predictors of future performance are trailing multiples (P/E and P/BV, above all), implying that prices fully incorporate analysts' forecasts. When these consensus forecasts give rise to valuation errors, they cannot be exploited to identify future equity returns. Moreover, combining multiples significantly improves performance prediction for undervalued banks.

We therefore select equally weighted portfolios including the top (bottom) decile of banks that each year at the end of April exhibit the largest positive (negative) valuation errors yielded by each multiple and by a set of multiple combinations. Retaining these portfolios for the following year, we compute the resulting annual returns. Each year this portfolio sorting is repeated until the last year of the time horizon under consideration.[16] We investigate ten combinations of multiples: nine that equally weight two different multiples, and one that aggregates P/BV, historical P/E, P/revenue, and P/customer deposits, each with a 25% weight. We present here the outcomes, over one year, of three main investment strategies: a long strategy on undervalued banks only, a second strategy going long on undervalued banks and shorting the market, and a third long-short strategy that invests half of the portfolio long on undervalued banks and the remainder short on overvalued banks.

Table 6 shows investment results for a trading strategy going long on undervalued banks, displaying annual raw, not market-adjusted, portfolio returns.

[insert Table 6 about here]

The best combined multiples strategies are historical P/E with P/B and the combination of the four metrics: P/E, P/B, P/revenue, and P/customer deposits. The risk-return profiles for these combinations are similar, as the efficiency ratios confirm. Although the combination of four multiples shows a higher return on average, it also displays a larger drop in the worst year of the last market crash (2009). The worst performance, in terms of risk-return, results from combinations involving the forward P/E (FY2), an outcome that is consistent with the previous correlation results. Multiples based on consensus forecasts perform well for predicting actual market prices, but are quite poor at identifying undervalued banks. All the strategies obtain high average returns compared to those of the market (S&P 500 index), but at the expense of more volatility.

[16] Transaction costs on rebalancing are not considered. Portfolio returns are thus gross returns.

Table 7 shows investment results for the strategy going long on undervalued firms and shorting the market. The buy-and-hold portfolio returns exhibited in the table are basically market-adjusted returns.

[insert Table 7 about here]

The annual average portfolio return ranges from a minimum of 14% to the best case (the four-multiples combination) of 24%. The portfolios of severely undervalued banks behave differently from the market. The efficiency ratios are always lower than those of the long-only portfolios, although the strategies tested maintain a risk-adjusted return profile higher than that of the market index, which is equal to 0.48. Hedging by going short on the market is effective during the subprime financial crisis (2008–2009) but not during the years of the dot-com bubble burst (1999–2000).

Finally, Table 8 displays the superior results arising from a long-short strategy, hedging the downside risk of long portfolios through going short on overvalued banks (using a 50%-50% portfolio allocation).

[insert Table 8 about here]

The main finding is a generalized significant reduction of the investment risk. Excluding the two combinations involving forward-looking P/Es, efficiency increases by 60% on average. As the fall in risk more than compensates for the widespread reduction of return, this strategy improves the efficiency ratios for all multiple combinations. The same is true for drawdown; even in the worst year, trailing P/E combined with P/revenue, P/E combined with P/customer deposits, and the combination of P/E, P/TBV, P/revenue, and P/customer deposits still yield a positive return.

Additionally, combining P/revenue with trailing P/E yields lower risk and superior efficiency. A marked improvement in performance arises for trailing P/E in combination with P/customer deposits. Revenue and customer deposits identify overvalued banks, and their combination with trailing P/E matches that of P/TBV and P/BV. This evidence indicates that those multiple combinations can also select overvalued banks. Overall, these market-neutral strategies perform notably better than the risk-adjusted return of the market index (0.48).

The strategy of taking a long position on undervalued firms performs substantially better than the market, but the performance deteriorates when one combines taking a long position on undervalued bank stocks and taking a short position on the market. The explanation for this counterintuitive result can be found in the concept of sector-specific risk. Long-short investment strategies are effective if there is both a performance differential and also a very high correlation between the long and short components. In this context, the high correlation makes it possible to neutralize fluctuations in yields and hence prices in a synchronized manner. If there is a consistent performance differential, but not a good correlation, the results for the whole portfolio deteriorate considerably. More specifically, the portfolio's risk deteriorates. In our case the low correlation is linked to the differences between the banking sector and the market as a whole, and therefore to its specific risk component, which would render a long-short hedging strategy ineffective.

6. Conclusions

Our results show that multiples yield significantly more accurate valuations for U.S. banks than for European ones, and that small retail and investment banks are more complex to evaluate than large retail banks. Forward P/E multiples vastly outperform historical P/E multiples, and multiples based on two-year-ahead forecasts (not just one year ahead) are strongly more accurate. Despite practitioners' belief, P/TBV is not more meaningful and precise than P/BV; and P/common dividends is a more precise tool than P/total dividends. Predictably, P/bank deposits appears to be accurate for valuing investment banks, whereas P/customer deposits is better for valuing commercial banks. Both the dot-com bubble crash and the subprime financial crisis negatively affected the reliability of relative bank valuations using multiples. Multiples' precision varies considerably over time, but all multiples perform in a correlated way.

The correlations between valuations in the top and bottom tails of the error distributions and the same banks' equity prices one year later show that overvalued financial institutions often remain overpriced, whereas P/BV, P/TBV, and particularly trailing P/E regularly predict positive price changes for the right tail of undervalued companies. Combining equally weighted multiples yields substantial improvements in predicting the performance of undervalued banks but not overvalued ones: no multiple or combination of multiples that we tested can predict a systematic downward price movement.

The outcomes of our portfolio analysis confirm the discriminating power of relative valuation for investment purposes. Unexpectedly, multiples involving forward-looking P/E yield the worst risk-adjusted return. Historical multiples (trailing P/E, P/BV, P/current deposits and P/revenue) perform better for all three buy-and-hold portfolios: one with a long strategy on undervalued banks, one going long on undervalued banks and shorting the market, and one with a long-short strategy that invests half of the portfolio long on undervalued banks and the remainder short on overvalued banks. Combinations of multiples appear well able to identify substantially undervalued banks, with average annual returns ranging from 22% to 33% for the long-only strategies and from 14% to 24% in excess of the market index. The performance of the long-short portfolios confirms the satisfactory results with an increase in efficiency ratios of approximately 60%. A market-neutral strategy reduces the risk considerably. For three of the ten strategies, there is no loss in a 22-year investment time span.

In discussing our findings we have to consider two important cautions. The first involves the implied assertion of market efficiency. Our yardstick for valuation accuracy is the current price. Market prices are supposed to correctly incorporate fundamentals. Our results should also hold if the pricing of fundamentals is accurate on *average*, implying that investors do not overweight or underweight one fundamental in relation to others (for example, earnings versus book value), or if deviations from fundamental value are not correlated to the predicted values.

Nevertheless, many empirical studies show that market prices may not fully reflect all available information. Some of our findings may not hold if deviations from intrinsic value change systematically across appraisal methods. For example, if values estimated through the earnings fundamental are strongly correlated to these mispricings, their predicted accuracy may be overstated. In our portfolio returns tests, we abandon the assumption of market efficiency.

Second, our aim is to survey comprehensive patterns, and accordingly, we may certainly overlook some more elusive relations that can be found in studies with smaller samples. We are aware that using large datasets may diminish the accuracy of multiples, since scholars choose comparable firms in a fairly strict framework, basically considering only industry, size, and/or business segment, while practitioners instead may pick comparable firms more sensibly and make allowances for additional firm-specific features such as growth, profitability, risk profile, and leverage. However, the actual valuation model used by investors is basically not observable, and it is not easy to integrate into large-sample empirical investigations.

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Table 1

Banks sample: Descriptive statistics.

Panel A. Banks sample characteristics and geographical composition

	European banks sample				US banks sample			
Listed	131				503			
Delisted	41				275			
	EU IB	EU CB Large	EU CB Small	Total	US IB	US CB Large	US CB Small	Total
# of banks	33	69	70	172	31	373	374	778

Country	European delisted, sample frequency	Country	European listed, sample frequency
Belgium	2.4%	Austria	4.5%
Germany	11.9%	Belgium	3.8%
Spain	9.5%	Cyprus	3.0%
France	14.3%	Germany	12.9%
Greece	7.1%	Spain	9.1%
Ireland	2.4%	Finland	2.3%
Italy	40.5%	France	18.9%
Netherlands	4.8%	Greece	8.3%
Portugal	4.7%	Ireland	1.5%
Slovenia	2.4%	Italy	18.9%
	100.0%	Luxembourg	1.5%
		Malta	2.2%
		Netherlands	5.3%
		Portugal	3.0%
		Slovenia	1.5%
		Slovakia	3.0%
			100.0%

Panel B. Summary statistics of banks subsamples

	Total Assets	Gross Loans	Common Equity	Loans/TA (%)	Basic EPS with Extra	FY2 EPS Mean Est.
US Investment Banks						
Median	84,819	5,522	1,535	0.339	1.96	1.52
1st quartile	1,965	444	127	0.233	1.13	0.75
3rd quartile	1,000,800	234,200	83,060	0.366	2.93	2.50
US Large Commercial Banks						
Median	6,048	4,152	584	0.69	1.60	1.31
1st quartile	1,569	1,094	135	0.62	0.90	0.77
3rd quartile	1,505,940	986,200	112,023	0.74	2.31	1.97
US Small Commercial Banks						

Median	747	521	66	0.72	1.03	0.76
1st quartile	436	299	37	0.64	0.50	0.13
3rd quartile	278,556	188,535	23,016	0.78	1.52	1.30
European Investment Banks						
Median	4,605	598	482	0.21	0.90	0.80
1st quartile	681	76	92	0.06	0.15	0.31
3rd quartile	130,061	86,214	8,463	0.31	5.32	1.98
European Large Commercial Banks						
Median	74,315	45,715	3,495	0.67	1.20	0.52
1st quartile	35,461	24,828	1,440	0.60	0.31	0.20
3rd quartile	171,642	106,868	8,443	0.77	6.26	1.17
European Small Commercial Banks						
Median	4,194	2,775	221	0.73	0.38	0.15
1st quartile	1,495	1,025	31	0.57	0.13	0.00
3rd quartile	9,978	7,023	639	0.81	3.50	0.63

Notes: Panel A presents, for the whole sample, the total numbers of listed and delisted banks, and the number of banks by size (small or large) and business segment (investment [IB] or commercial [CB]). For European banks the table also shows the percentage of listed and delisted banks in the sample by country. Panel B shows basic descriptive statistics related to the subsamples of banks, across the entire time span 1990–2012. The banks are divided into investment, commercial large, and commercial small banks, as well as grouped by region (Europe or the Unite States). Commercial banks are those with a loans/total assets ratio above 0.4. Small and large banks are split by total assets, at the median of the whole sample of commercial banks. Data displayed in panel B are in US$ million except the last two columns, which are in US$. Raw data are taken from Compustat, except gross loans from Bankscope and forward (expected) (FY2) EPS from I/B/E/S.

Table 2

Banking multiples accuracy performance: U.S. and European banks subsamples.

	Valuations within x % of price:						Valuations within x % of price:				
	10%	25%	50%	75%	90%		10%	25%	50%	75%	90%
	EU IB						**US IB**				
P/E (FY1)	7.9%	31.5%	65.4%	89.0%	92.9%	P/E (FY1)	21.1%	46.6%	79.2%	92.5%	95.3%
P/E (FY2)	13.1%	39.2%	75.4%	93.1%	94.6%	P/E (FY2)	17.1%	47.7%	80.1%	93.0%	95.5%
P/Common Dividends	12.3%	33.3%	57.9%	78.9%	88.6%	P/Common Dividends	10.1%	28.2%	50.9%	70.3%	82.3%
P/Total Dividends	12.8%	29.1%	54.7%	76.9%	88.0%	P/Total Dividends	8.1%	23.6%	50.9%	72.4%	82.6%
P/BV	10.8%	27.4%	55.9%	86.6%	93.5%	P/BV	11.5%	30.8%	61.5%	85.6%	91.7%
P/TBV	12.3%	25.1%	52.5%	76.0%	87.2%	P/TBV	7.1%	25.3%	55.8%	80.1%	89.1%
P/Revenue	8.7%	19.6%	44.6%	69.6%	80.4%	P/Revenue	12.9%	31.0%	58.2%	77.2%	85.7%
P/Banks Deposits	12.1%	15.2%	21.2%	48.5%	51.5%	P/Customer Deposits	10.2%	24.3%	54.4%	79.7%	86.9%
P/Customer Deposits	2.5%	6.3%	17.5%	35.0%	41.3%	P/E (Diluted, with Extra)	12.4%	29.2%	56.6%	78.0%	86.4%
P/E (Basic, with Extra)	7.9%	23.0%	49.3%	74.3%	86.8%	P/E (Diluted, no Extra)	11.0%	28.9%	57.5%	78.3%	86.4%
P/E (Basic, no Extra)	6.8%	24.3%	47.3%	72.3%	86.5%	P/E (Basic, with Extra)	11.3%	28.3%	56.9%	78.0%	87.0%
	EU CB Large						**US CB Large**				
P/E (FY1)	23.2%	49.6%	77.7%	92.9%	96.0%	P/E (FY1)	32.9%	65.2%	88.0%	94.8%	96.9%
P/E (FY2)	24.7%	57.3%	84.9%	95.8%	97.4%	P/E (FY2)	34.3%	68.9%	89.8%	95.4%	97.1%
P/Common Dividends	10.3%	28.2%	53.6%	73.8%	83.7%	P/Common Dividends	13.3%	32.2%	58.7%	77.3%	87.2%
P/Total Dividends	10.5%	28.0%	50.9%	71.6%	81.8%	P/Total Dividends	13.1%	33.3%	60.0%	77.5%	87.0%
P/BV	7.8%	19.7%	49.1%	75.7%	82.6%	P/BV	15.4%	38.4%	66.1%	83.2%	89.8%
P/TBV	5.5%	17.4%	45.0%	74.3%	81.7%	P/TBV	13.2%	33.5%	63.7%	81.3%	88.8%
P/Revenue	6.8%	17.3%	42.6%	71.8%	82.9%	P/Revenue	11.6%	30.6%	59.3%	82.2%	89.8%
P/Banks Deposits	8.7%	13.5%	32.2%	53.8%	66.8%	P/Customer Deposits	13.0%	31.1%	60.5%	82.0%	88.6%
P/Customer Deposits	7.0%	21.8%	47.9%	67.4%	78.4%	P/E (Diluted, with Extra)	15.7%	37.8%	65.6%	82.4%	89.1%
P/E (Basic, with Extra)	13.6%	35.1%	64.2%	77.8%	88.5%	P/E (Diluted, no Extra)	16.0%	38.0%	65.6%	82.4%	89.1%
P/E (Basic, no Extra)	13.7%	32.0%	64.0%	76.3%	86.0%	P/E (Basic, with Extra)	16.0%	37.9%	65.5%	82.3%	89.1%
	EU CB Small						**US CB Small**				
P/E (FY1)	13.9%	37.8%	68.9%	88.3%	94.4%	P/E (FY1)	28.5%	59.5%	84.4%	93.2%	96.5%
P/E (FY2)	15.9%	45.3%	70.6%	89.4%	94.1%	P/E (FY2)	30.5%	62.9%	86.9%	94.3%	96.6%
P/Common Dividends	7.6%	14.0%	37.3%	58.5%	69.9%	P/Common Dividends	15.2%	36.2%	61.5%	81.1%	88.8%
P/Total Dividends	7.5%	14.1%	35.3%	57.7%	70.1%	P/Total Dividends	15.9%	36.2%	62.0%	80.5%	88.1%
P/BV	1.9%	4.0%	11.0%	32.3%	71.5%	P/BV	18.6%	45.4%	76.5%	88.5%	92.4%
P/TBV	1.9%	4.0%	9.7%	29.6%	68.8%	P/TBV	18.0%	44.4%	75.3%	88.0%	91.9%
P/Revenue	3.8%	8.9%	19.4%	44.1%	76.6%	P/Revenue	13.7%	34.4%	65.7%	83.9%	89.9%
P/Banks Deposits	3.8%	3.8%	11.4%	27.6%	44.8%	P/Customer Deposits	14.7%	35.6%	65.5%	84.0%	90.0%
P/Customer Deposits	3.6%	9.7%	21.7%	46.0%	73.3%	P/E (Diluted, with Extra)	14.7%	36.9%	66.0%	82.9%	89.1%
P/E (Basic, with Extra)	3.0%	13.2%	30.3%	57.3%	75.6%	P/E (Diluted, no Extra)	14.6%	36.9%	65.8%	83.0%	89.1%
P/E (Basic, no Extra)	2.6%	13.2%	30.3%	57.7%	75.6%	P/E (Basic, with Extra)	14.2%	36.7%	66.0%	82.8%	89.2%

Notes: Errors are computed using the method discussed in section 4.2. We compute errors as the difference between the inferred price and the actual price of the stock on April 30, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure and multiplying it by each relevant value driver. The table highlights the percentage of banks having valuations within 10%, 25%, 50%, 75%, and 95% of their actual price. Bank subsamples are based on size (small or large) and business segment (investment [IB] or commercial [CB]). Valuation errors (scaled by share price) are computed for every firm-year using harmonic means of firms in each subsample. Sample banks are collected in April each year between 1990 and 2012.

Table 3

The effects of the subprime financial crisis on banking multiples' accuracy.

Panel A. European banks subsamples

Valuation within x% of price	Before financial crisis (1990–2007) (A)					During crisis (2008–2012) (B)					Difference (B-A)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
								EU IB							
P/E (FY1)	4.7%	25.6%	72.1%	93.0%	95.3%	9.5%	34.5%	61.9%	86.9%	91.7%	4.9%	8.9%	-10.2%	-6.1%	-3.7%
P/E (FY2)	7.0%	20.9%	72.1%	95.3%	97.7%	16.1%	48.3%	77.0%	92.0%	93.1%	9.1%	27.3%	4.9%	-3.4%	-4.6%
P/Common Dividends	9.0%	25.4%	49.3%	73.1%	83.6%	17.0%	44.7%	70.2%	87.2%	95.7%	8.1%	19.3%	21.0%	14.1%	12.2%
P/Total Dividends	10.4%	23.9%	49.3%	73.1%	83.6%	16.0%	36.0%	62.0%	82.0%	94.0%	5.6%	12.1%	12.7%	8.9%	10.4%
P/BV	12.9%	30.1%	54.8%	79.6%	91.4%	8.6%	24.7%	57.0%	93.5%	95.7%	-4.3%	-5.4%	2.2%	14.0%	4.3%
P/TBV	11.5%	21.8%	50.6%	73.6%	88.5%	13.0%	28.3%	54.3%	78.3%	85.9%	1.5%	6.4%	3.8%	4.7%	-2.6%
P/Revenue	7.4%	16.8%	42.1%	65.3%	77.9%	10.1%	22.5%	47.2%	74.2%	83.1%	2.7%	5.6%	5.1%	8.9%	5.3%
P/Banks Deposits	11.5%	15.4%	19.2%	53.8%	53.8%	14.3%	14.3%	28.6%	28.6%	42.9%	2.7%	-1.1%	9.3%	-25.3%	-11.0%
P/Customer Deposits	4.3%	6.4%	14.9%	40.4%	51.1%	0.0%	6.1%	21.2%	27.3%	27.3%	-4.3%	-0.3%	6.3%	-13.2%	-23.8%
P/E (Basic, with Extra)	5.2%	20.8%	46.8%	70.1%	84.4%	10.7%	25.3%	52.0%	78.7%	89.3%	5.5%	4.6%	5.2%	8.5%	4.9%
P/E (Basic, no Extra)	4.1%	21.6%	45.9%	67.6%	85.1%	9.5%	27.0%	48.6%	77.0%	87.8%	5.4%	5.4%	2.7%	9.5%	2.7%
								EU CB Large							
P/E (FY1)	27.3%	59.0%	82.3%	95.2%	97.2%	18.1%	37.7%	71.9%	89.9%	94.5%	-9.2%	-21.3%	-10.5%	-5.2%	-2.7%
P/E (FY2)	28.3%	66.9%	87.3%	97.6%	98.4%	20.4%	45.6%	82.0%	93.7%	96.1%	-7.9%	-21.3%	-5.2%	-3.9%	-2.3%
P/Common Dividends	8.9%	27.2%	51.7%	71.7%	82.8%	13.9%	30.6%	58.3%	79.2%	86.1%	5.0%	3.3%	6.7%	7.5%	3.3%
P/Total Dividends	7.7%	26.4%	51.1%	70.3%	81.9%	16.1%	31.2%	50.5%	74.2%	81.7%	8.4%	4.8%	-0.6%	3.9%	-0.1%
P/BV	6.8%	17.9%	45.0%	72.5%	80.1%	9.2%	22.2%	54.6%	80.0%	85.9%	2.4%	4.2%	9.6%	7.5%	5.9%
P/TBV	4.8%	15.5%	39.4%	69.7%	78.9%	6.5%	20.0%	52.4%	80.5%	85.4%	1.7%	4.5%	13.0%	10.8%	6.5%
P/Revenue	6.4%	15.1%	41.0%	71.3%	82.1%	7.4%	20.2%	44.7%	72.3%	84.0%	1.1%	5.1%	3.6%	1.0%	2.0%
P/Banks Deposits	7.6%	12.4%	29.7%	50.3%	64.3%	17.4%	21.7%	52.2%	82.6%	87.0%	9.8%	9.3%	22.4%	32.3%	22.6%
P/Customer Deposits	5.6%	18.5%	43.8%	61.4%	74.7%	9.0%	26.6%	53.7%	75.7%	83.6%	3.4%	8.1%	9.9%	14.3%	8.9%
P/E (Basic, with Extra)	12.8%	36.2%	65.2%	76.6%	87.2%	14.5%	34.1%	63.0%	79.0%	89.9%	1.7%	-2.1%	-2.2%	2.4%	2.6%
P/E (Basic, no Extra)	13.5%	34.0%	67.4%	76.6%	85.1%	13.9%	29.9%	60.6%	75.9%	86.9%	0.4%	-4.1%	-6.8%	-0.7%	1.8%
								EU CB Small							
P/E (FY1)	16.1%	42.7%	70.2%	89.5%	96.8%	8.9%	26.8%	66.1%	85.7%	89.3%	-7.2%	-16.0%	-4.1%	-3.8%	-7.5%
P/E (FY2)	18.3%	51.3%	69.6%	90.4%	94.8%	10.9%	32.7%	72.7%	87.3%	92.7%	-7.4%	-18.6%	3.2%	-3.2%	-2.1%
P/Common Dividends	9.0%	16.8%	34.8%	57.4%	67.1%	4.9%	8.6%	42.0%	60.5%	75.3%	-4.1%	-8.1%	7.1%	3.1%	8.2%
P/Total Dividends	8.4%	14.8%	32.3%	57.4%	67.7%	5.8%	12.8%	40.7%	58.1%	74.4%	-2.6%	-2.0%	8.4%	0.7%	6.7%
P/BV	3.3%	6.0%	15.3%	40.5%	74.4%	0.0%	1.3%	5.1%	21.0%	67.5%	-3.3%	-4.8%	-10.3%	-19.4%	-6.9%
P/TBV	3.3%	6.5%	14.0%	37.7%	71.6%	0.0%	0.6%	3.8%	18.5%	65.0%	-3.3%	-5.9%	-10.1%	-19.2%	-6.7%
P/Revenue	3.7%	10.2%	22.8%	47.0%	78.1%	3.8%	7.0%	14.6%	40.1%	74.5%	0.1%	-3.2%	-8.1%	-6.8%	-3.6%
P/Banks Deposits	4.1%	4.1%	12.4%	29.9%	47.4%	0.0%	0.0%	0.0%	0.0%	12.5%	-4.1%	-4.1%	-12.4%	-29.9%	-34.9%
P/Customer Deposits	3.8%	13.3%	28.0%	51.7%	74.9%	3.4%	4.7%	12.8%	37.8%	70.9%	-0.4%	-8.5%	-15.1%	-13.8%	-3.9%
P/E (Basic, with Extra)	0.0%	8.7%	25.2%	63.0%	88.2%	6.5%	18.7%	36.4%	50.5%	60.7%	6.5%	10.0%	11.3%	-12.5%	-27.4%
P/E (Basic, no Extra)	0.0%	8.7%	25.2%	63.0%	88.2%	5.6%	18.7%	36.4%	51.4%	60.7%	5.6%	10.0%	11.3%	-11.6%	-27.4%

Panel B. U.S. banks subsamples

Valuation within x% of price	Before financial crisis (1990–2007) (A)					During crisis (2008–2012) (B)					Difference (B-A)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
US IB															
P/E (FY1)	22.3%	47.9%	79.6%	92.9%	95.7%	17.6%	42.6%	77.9%	91.2%	94.1%	-4.6%	-5.2%	-1.7%	-1.7%	-1.6%
P/E (FY2)	19.0%	51.2%	83.4%	94.3%	96.2%	11.8%	38.2%	71.1%	89.5%	93.4%	-7.1%	-13.0%	-12.4%	-4.8%	-2.8%
P/Common Dividends	9.5%	26.2%	49.6%	69.4%	82.9%	12.5%	35.9%	56.3%	73.4%	79.7%	3.0%	9.7%	6.6%	4.0%	-3.2%
P/Total Dividends	8.7%	23.0%	48.8%	71.0%	81.7%	5.7%	25.7%	58.6%	77.1%	85.7%	-3.0%	2.7%	9.8%	6.1%	4.0%
P/BV	10.6%	28.0%	58.5%	82.9%	90.2%	15.2%	40.9%	72.7%	95.5%	97.0%	4.6%	12.9%	14.2%	12.5%	6.7%
P/TBV	8.5%	27.2%	54.9%	80.5%	89.0%	1.5%	18.2%	59.1%	78.8%	89.4%	-7.0%	-9.1%	4.2%	-1.7%	0.4%
P/Revenue	12.5%	29.6%	55.1%	74.9%	83.6%	14.3%	36.4%	70.1%	85.7%	93.5%	1.7%	6.7%	15.1%	10.8%	9.9%
P/Customer Deposits	7.4%	21.8%	50.2%	77.8%	86.8%	21.0%	33.9%	71.0%	87.1%	87.1%	13.6%	12.1%	20.8%	9.3%	0.3%
P/E (Diluted, with Extra)	12.5%	30.2%	56.2%	76.2%	84.7%	12.3%	24.6%	58.5%	86.2%	93.8%	-0.1%	-5.6%	2.2%	10.0%	9.1%
P/E (Diluted, no Extra)	10.7%	29.3%	57.1%	76.8%	85.0%	12.1%	27.3%	59.1%	84.8%	92.4%	1.4%	-2.0%	1.9%	8.1%	7.4%
P/E (Basic, with Extra)	11.0%	28.5%	56.6%	76.2%	85.4%	12.3%	27.7%	58.5%	86.2%	93.8%	1.3%	-0.8%	1.9%	10.0%	8.4%
P/E (Basic, no Extra)	11.1%	28.6%	56.4%	76.4%	85.4%	13.6%	28.8%	59.1%	84.8%	92.4%	2.6%	0.2%	2.7%	8.4%	7.1%
US CB Large															
P/E (FY1)	37.2%	70.8%	91.8%	96.3%	97.8%	18.7%	46.9%	75.5%	89.7%	93.9%	-18.5%	-23.9%	-16.3%	-6.6%	-3.9%
P/E (FY2)	38.6%	75.3%	93.4%	97.1%	98.1%	22.1%	50.4%	79.3%	90.5%	94.1%	-16.5%	-24.9%	-14.1%	-6.6%	-4.0%
P/Common Dividends	13.2%	32.8%	60.2%	78.2%	87.1%	13.7%	29.4%	52.3%	73.7%	87.8%	0.5%	-3.4%	-7.9%	-4.5%	0.7%
P/Total Dividends	12.7%	32.2%	59.3%	77.0%	86.2%	14.5%	37.5%	62.6%	79.6%	89.7%	1.9%	5.4%	3.3%	2.6%	3.5%
P/BV	15.2%	36.9%	63.3%	82.5%	89.7%	16.2%	44.0%	76.7%	85.8%	90.2%	1.0%	7.1%	13.3%	3.2%	0.5%
P/TBV	13.3%	32.8%	60.9%	80.1%	88.7%	12.7%	36.3%	74.7%	85.8%	89.4%	-0.6%	3.6%	13.8%	5.7%	0.7%
P/Revenue	13.0%	33.6%	61.4%	82.0%	89.9%	6.6%	19.6%	51.8%	82.7%	89.2%	-6.4%	-14.0%	-9.6%	0.7%	-0.7%
P/Customer Deposits	14.5%	33.9%	62.3%	81.7%	88.6%	7.6%	20.8%	54.1%	83.2%	88.8%	-6.9%	-13.0%	-8.2%	1.5%	0.2%
P/E (Diluted, with Extra)	15.3%	37.3%	65.3%	81.9%	88.4%	17.9%	40.7%	67.3%	85.1%	92.2%	2.5%	3.4%	1.9%	3.3%	3.8%
P/E (Diluted, no Extra)	15.8%	37.5%	65.5%	81.9%	88.5%	17.4%	40.5%	66.3%	85.0%	92.1%	1.6%	3.0%	0.8%	3.1%	3.6%
P/E (Basic, with Extra)	15.6%	37.3%	65.1%	81.7%	88.5%	17.9%	40.7%	67.4%	85.3%	92.2%	2.2%	3.3%	2.3%	3.6%	3.7%
P/E (Basic, no Extra)	16.2%	37.5%	65.3%	81.8%	88.5%	16.5%	40.8%	66.4%	85.0%	92.4%	0.4%	3.3%	1.1%	3.2%	3.9%
US CB Small															
P/E (FY1)	32.2%	65.8%	89.3%	96.0%	97.7%	17.9%	41.2%	70.1%	85.0%	93.1%	-14.3%	-24.6%	-19.2%	-10.9%	-4.7%
P/E (FY2)	35.4%	70.9%	93.1%	97.6%	98.2%	20.2%	46.3%	73.9%	87.6%	93.2%	-15.2%	-24.6%	-19.2%	-10.0%	-5.0%
P/Common Dividends	15.7%	37.4%	63.0%	81.7%	88.2%	13.2%	31.2%	55.3%	78.9%	91.1%	-2.5%	-6.2%	-7.7%	-2.8%	2.9%
P/Total Dividends	15.8%	37.1%	62.5%	80.6%	87.6%	16.2%	33.3%	60.2%	79.8%	89.7%	0.4%	-3.8%	-2.3%	-0.8%	2.1%
P/BV	19.0%	45.7%	76.2%	88.0%	91.7%	17.5%	44.4%	77.7%	90.3%	94.8%	-1.4%	-1.3%	1.6%	2.3%	3.1%
P/TBV	18.1%	44.6%	75.3%	87.8%	91.5%	17.3%	43.5%	75.6%	88.8%	93.5%	-0.8%	-1.2%	0.3%	1.0%	2.0%
P/Revenue	14.7%	36.3%	68.1%	84.5%	90.0%	10.5%	28.3%	57.9%	82.0%	89.3%	-4.2%	-8.0%	-10.2%	-2.5%	-0.8%
P/Customer Deposits	15.3%	37.0%	66.6%	84.0%	90.0%	12.8%	31.0%	61.6%	84.0%	90.2%	-2.5%	-6.0%	-4.9%	0.0%	0.2%
P/E (Diluted, with Extra)	14.2%	36.6%	66.9%	83.6%	88.8%	16.7%	37.9%	61.7%	79.7%	90.2%	2.4%	1.2%	-5.2%	-3.9%	1.3%
P/E (Diluted, no Extra)	14.2%	36.6%	66.8%	83.7%	88.9%	16.7%	38.5%	61.5%	79.7%	89.9%	2.5%	1.9%	-5.3%	-4.0%	1.1%
P/E (Basic, with Extra)	13.7%	36.4%	66.8%	83.4%	88.8%	16.1%	38.4%	61.9%	79.9%	90.9%	2.4%	2.1%	-4.9%	-3.5%	2.1%
P/E (Basic, no Extra)	13.6%	36.7%	66.7%	83.7%	88.8%	16.1%	38.5%	61.9%	79.7%	90.3%	2.5%	1.8%	-4.9%	-4.0%	1.5%

Notes: We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure and multiplying it by each relevant value driver. Comparable firms are selected from the peer group. The table highlights the yearly average percentage of banks in each subsample having valuations within 10%, 25%, 50%, 75%, and 95% of their price. Valuation errors (scaled by share price) are computed for every firm-year using the harmonic means of firms in each subsample. Subsamples are based on size (small or large) and business segment (investment [IB] or commercial [CB]). Sample banks are collected in April each year between 1990 and 2012. The last five columns of the table show the difference between averages for the precrisis period and values for financial crisis years. Negative values of these differences indicate multiples that were performing better before the financial crisis.

Table 4

Correlation analysis: single multiples.

	P/E (FY1)	P/E (FY2)	P/Com D	P/BV	P/TBV	P/Rev	P/Cust Dep	P/E (Basic, no Extra)
Panel A. Positive Tail (Undervalued Banks)								
1990	0.27	0.43	*-0.74*	*-0.11*	*-0.18*	0.35	0.13	0.37
1991	0.52	0.58	*-0.09*	0.30	0.36	*-0.12*	0.74	0.02
1992	*-0.17*	0.02	*-0.67*	0.28	0.11	0.13	0.26	*-0.46*
1993	0.46	0.38	0.25	0.46	0.48	0.46	0.57	0.45
1994	*-0.43*	*-0.22*	0.08	0.05	0.38	0.36	0.30	0.25
1995	0.41	0.18	0.13	0.25	0.29	0.28	0.49	0.28
1996	*-0.09*	*-0.15*	0.09	0.44	0.21	*-0.10*	0.24	0.43
1997	0.05	*-0.04*	0.10	0.19	0.25	0.14	0.19	0.19
1998	*-0.52*	*-0.53*	0.19	0.24	0.11	0.15	0.04	0.02
1999	*-0.04*	*-0.10*	*-0.17*	*-0.07*	*-0.05*	*-0.13*	*-0.09*	0.01
2000	*-0.07*	0.01	*-0.15*	0.20	0.12	0.11	0.05	0.14
2001	*-0.19*	*-0.16*	*-0.07*	0.09	0.11	0.13	0.29	0.17
2002	*-0.08*	0.11	0.15	*0.00*	0.12	*-0.25*	*-0.19*	0.27
2003	0.16	0.16	0.32	0.23	0.08	0.63	0.64	0.03
2004	0.01	0.11	*-0.04*	*-0.01*	*-0.07*	*-0.19*	*-0.05*	*-0.26*
2005	*-0.02*	*-0.06*	0.48	*0.00*	*-0.01*	*-0.13*	0.11	*-0.01*
2006	*-0.22*	*-0.15*	*-0.06*	0.23	0.01	*-0.35*	*-0.24*	0.20
2007	0.01	0.14	0.08	0.08	*-0.03*	*-0.20*	*-0.21*	0.03
2008	0.08	0.06	*-0.07*	0.39	0.06	*-0.02*	*-0.25*	*-0.08*
2009	*-0.34*	*-0.28*	0.30	0.11	*-0.02*	0.27	0.01	0.34
2010	*-0.22*	0.04	*-0.08*	*-0.13*	*-0.12*	*-0.27*	*-0.23*	0.05
2011	*-0.20*	*-0.30*	*-0.23*	0.35	0.35	0.22	0.28	*-0.04*
# Obs. > 0	9	12	11	16	15	12	15	17
# Obs. < 0	13	10	11	6	7	10	7	5
Panel B. Negative Tail (Overvalued Banks)								
1990	0.50	*-0.28*	*-0.68*	0.31	0.20	0.02	0.20	0.42
1991	0.27	*-0.30*	*-0.67*	0.26	0.12	*-0.06*	*0.00*	*-0.67*
1992	0.64	*-0.58*	0.38	*-0.10*	0.08	0.47	*-0.23*	0.33
1993	*-0.09*	0.24	*-0.33*	0.05	*-0.03*	0.22	0.23	0.12
1994	*-0.46*	*-0.37*	*0.00*	*-0.31*	*-0.38*	*-0.17*	*-0.05*	*-0.04*
1995	0.37	*-0.34*	*-0.25*	*-0.02*	*0.00*	*-0.05*	*-0.10*	*-0.12*
1996	*-0.11*	*-0.36*	*-0.03*	*-0.05*	*-0.07*	0.06	0.06	0.18
1997	0.16	0.51	0.18	*-0.17*	*-0.16*	*-0.18*	*-0.15*	*-0.09*
1998	0.30	*-0.66*	0.03	0.21	0.12	0.04	0.11	0.04
1999	0.14	0.11	*-0.04*	0.02	0.27	0.14	0.24	0.18
2000	*-0.11*	*-0.13*	0.11	*-0.07*	0.17	*-0.11*	*-0.01*	*-0.19*
2001	*-0.42*	*-0.08*	0.08	*-0.31*	*-0.12*	*-0.34*	*-0.16*	*-0.14*
2002	0.30	0.26	*-0.08*	*-0.32*	*-0.35*	*-0.27*	*-0.43*	*-0.25*
2003	*-0.23*	*-0.65*	0.04	*-0.17*	*-0.21*	*-0.18*	*-0.20*	*-0.08*
2004	0.20	0.28	*-0.24*	*-0.18*	*-0.10*	*-0.08*	0.03	*-0.17*

2005	0.15	0.51	*-0.25*	0.09	0.01	*-0.08*	*-0.10*	0.31
2006	*-0.26*	*-0.30*	0.07	*-0.09*	0.04	0.16	0.19	0.12
2007	*-0.25*	0.06	0.25	0.48	0.30	0.51	0.45	0.16
2008	*-0.09*	0.14	0.36	0.33	0.28	0.51	0.44	0.14
2009	*-0.12*	0.01	0.44	0.52	0.58	0.58	0.53	*-0.02*
2010	*0.00*	*-0.16*	0.09	0.45	0.51	0.47	0.45	0.02
2011	0.14	*-0.10*	0.10	0.28	0.44	0.32	0.24	0.14
# Obs. > 0	11	9	12	11	13	12	12	12
# Obs. < 0	11	13	10	11	9	10	10	10

Notes: The table displays Pearson correlation coefficients for distribution errors in the positive (Panel A) and negative (Panel B) tails, for U.S. banks only. Correlation coefficients are computed between the top (undervalued banks) and bottom (overvalued banks) distribution deciles of the valuation errors and subsequent one-year market-adjusted stock returns. Errors are based on single-multiple metrics. Valuation errors (scaled by share price) are computed for every firm-year using the harmonic means of firms in each subsample. Sample banks are collected in April each year between 1990 and 2012. The last rows of each panel give the number of positive and negative correlations throughout the years examined for a given multiple. Negative correlations, which discredit or at least limit the multiples' utility as an investing criterion, are highlighted in italic.

Table 5

Correlation analysis: combinations of multiples.

	P/BV & P/E (Basic, no Extra)	P/TBV & P/E (Basic, no Extra)	P/BV & P/E (FY2)	P/TBV & P/E (FY2)	P/Customer Deposits & P/E (Basic, no Extra)	P/Revenue & P/E (Basic, no Extra)	P/TBV & P/Total Dividends	P/BV & P/E (Basic, no Extra) & P/Revenue & P/Customer Deposits
Panel A. Positive Tail (Undervalued Banks)								
1990	0.35	0.47	0.49	*-0.01*	0.38	0.24	*-0.9*	0.22
1991	0.15	0.25	0.38	0.66	0.26	*-0.13*	*-0.2*	*-0.27*
1992	0.17	0.21	*-0.24*	*-0.39*	0.01	0.2	*-0.67*	0.34
1993	0.57	0.56	0.29	0.28	0.62	0.6	*-0.06*	0.7
1994	0.29	0.22	*-0.01*	0.05	0.26	0.3	0.35	0.36
1995	0.28	0.29	0.23	0.39	0.27	0.32	0.13	0.38
1996	0.22	0.31	0.16	*-0.36*	0.29	0.19	0.32	0.3
1997	0.18	0.2	0.08	0.1	0.35	0.28	0.1	0.28
1998	0.12	0.18	0.32	0.24	0.21	0.14	0.07	0.17
1999	*-0.03*	*-0.02*	*-0.15*	*-0.12*	0.01	0	*-0.03*	*-0.01*
2000	0.11	0.13	0.18	0.14	0.11	0.11	*-0.13*	0.07
2001	0.34	0.28	0.1	0.16	0.28	0.35	*-0.1*	0.36
2002	0.16	0.25	0.33	0.21	0.22	0.21	0.06	0.21
2003	0.16	0.08	0.27	0.01	0.63	0.7	0.28	0.66
2004	*-0.19*	*-0.17*	*-0.05*	*-0.08*	*-0.15*	*-0.24*	*-0.21*	*-0.19*
2005	*-0.03*	0.01	0.01	0.1	0.08	*-0.1*	0.21	*-0.04*
2006	0.29	0.25	0.04	*-0.14*	*-0.07*	0.24	0.08	0.08
2007	0.07	0.1	*-0.07*	*-0.03*	0.07	0.19	0.26	0.13
2008	0.53	0.41	0.51	0.42	*-0.07*	0.49	*-0.29*	*-0.07*
2009	0.33	0.31	*-0.02*	*-0.05*	0.35	0.33	0.32	0.33
2010	0.18	0.21	*-0.01*	0.02	0.13	0.12	0.05	0.09
2011	*-0.01*	*-0.05*	*-0.11*	0	0.05	0.11	*-0.31*	0.12
# Obs. > 0	18	19	14	14	19	19	12	17
# Obs. < 0	4	3	8	8	3	3	10	5
Panel B. Negative Tail (Overvalued Banks)								
1990	0.32	0.49	0.58	0.57	0.59	0.31	*-0.15*	0.38
1991	*-0.17*	*-0.28*	0.36	0.51	*-0.38*	*-0.36*	0.24	*-0.26*
1992	0.51	0.06	0.72	0.55	0.31	0.44	0.1	0
1993	0.32	0.28	*-0.25*	*-0.25*	0.19	0.17	0.2	0.2
1994	*-0.19*	*-0.21*	*-0.28*	*-0.39*	*-0.33*	*-0.34*	0.08	*-0.2*
1995	0.08	0.16	0.17	*-0.18*	*-0.07*	0.04	*-0.15*	*-0.19*
1996	*-0.07*	*-0.06*	0.23	0.18	0.05	0	0.04	*-0.01*
1997	*-0.17*	*-0.15*	0.59	0.59	*-0.22*	*-0.25*	*-0.07*	*-0.14*
1998	0.01	0.08	0.07	0.25	0.16	0.08	0.07	0.26
1999	0.1	0.13	0.11	0.25	0.21	0.15	0.16	0.09
2000	*-0.26*	*-0.21*	*-0.23*	*-0.28*	*-0.14*	*-0.19*	0.19	*-0.14*
2001	*-0.18*	*-0.05*	*-0.32*	*-0.32*	*-0.29*	*-0.32*	*-0.06*	*-0.35*

2002	*-0.42*	*-0.38*	0.24	0.36	*-0.35*	*-0.33*	*-0.22*	*-0.37*
2003	*-0.19*	*-0.14*	*-0.3*	*-0.24*	*-0.03*	*-0.19*	*-0.09*	*-0.28*
2004	*-0.02*	*-0.25*	0.37	0.19	*-0.1*	*-0.07*	*-0.14*	*-0.28*
2005	*-0.05*	*-0.15*	*-0.41*	*-0.12*	*-0.2*	*-0.18*	0.21	*-0.13*
2006	0.17	0.17	*-0.01*	0.16	0.25	0.09	0.11	0.09
2007	0.19	0.27	0.16	*-0.04*	0.26	0.37	0.48	0.32
2008	0.22	0.34	*-0.07*	0.03	0.1	0.1	0.43	0.2
2009	0.2	0.21	0.14	0.27	*-0.11*	0.24	0.54	0.02
2010	0.01	*-0.05*	*-0.03*	0.27	*-0.31*	*-0.18*	0.72	*-0.18*
2011	0.17	0.01	*-0.03*	0.45	0.07	0.25	0.08	*-0.11*
# Obs. > 0	12	11	12	14	10	12	15	8
# Obs. < 0	10	11	10	8	12	10	7	14

Notes: The table displays Pearson correlation coefficients for distribution errors in the positive (Panel A) and negative (Panel B) tails, for U.S. banks only. Correlation coefficients are computed between the top (undervalued banks) and bottom (overvalued banks) distribution deciles of the valuation errors and subsequent market-adjusted one-year stock returns. Errors are based on combinations of two or more multiple metrics, equally weighted. Valuation errors (scaled by share price) are computed for every firm-year using the harmonic means of firms in each subsample. Sample banks are collected in April each year between 1990 and 2012. The last rows of each panel give the numbers of positive and negative correlations throughout the years examined for a given combination of multiples. Negative correlations, which discredit or at least limit the multiples' utility as an investing criterion, are highlighted in italic.

Table 6

Investment strategies: long strategy on undervalued banks only.

Year	P/BV & P/E (Basic, no Extra)	P/TBV & P/E (Basic, no Extra)	P/BV & P/E (FY2)	P/TBV & P/E (FY2)	P/Total Dividends & P/TBV	P/E (Basic, no Extra) & P/Customer Deposits	P/BV & P/Customer Deposits	P/Revenue & P/BV	P/E (Basic, no Extra) & P/Revenue	P/TBV & P/Revenue & P/Customer Deposits & P/E (Basic, no Extra)	S&P 500
1991	18%	18%	15%	21%	21%	19%	12%	17%	19%	19%	13%
1992	37%	33%	51%	59%	51%	41%	75%	63%	46%	63%	11%
1993	41%	41%	60%	60%	38%	45%	57%	61%	45%	61%	6%
1994	26%	26%	10%	10%	27%	27%	25%	25%	26%	25%	2%
1995	21%	23%	16%	18%	16%	20%	18%	19%	21%	18%	14%
1996	45%	44%	47%	47%	43%	46%	43%	41%	44%	44%	27%
1997	48%	46%	45%	40%	42%	46%	44%	44%	46%	44%	22%
1998	86%	85%	70%	68%	77%	81%	83%	80%	81%	77%	39%
1999	-16%	-19%	-23%	-26%	-18%	-19%	-19%	-20%	-16%	-18%	20%
2000	-5%	-5%	-5%	-5%	-10%	-5%	-3%	-4%	-7%	-2%	9%
2001	35%	34%	40%	42%	25%	32%	32%	34%	32%	35%	-14%
2002	45%	46%	41%	39%	44%	54%	46%	44%	49%	51%	-14%
2003	42%	39%	23%	28%	37%	42%	40%	37%	43%	43%	-15%
2004	60%	55%	59%	63%	36%	65%	64%	68%	61%	64%	21%
2005	15%	15%	15%	16%	6%	17%	16%	14%	14%	20%	4%
2006	34%	33%	22%	22%	18%	31%	25%	28%	31%	38%	13%
2007	6%	4%	0%	-1%	-3%	7%	2%	3%	8%	7%	13%
2008	-15%	-17%	-34%	-33%	-14%	-16%	-27%	-27%	-18%	-9%	-7%
2009	-20%	-21%	-47%	-46%	-40%	-28%	-53%	-47%	-24%	-30%	-37%
2010	68%	68%	54%	50%	70%	64%	46%	47%	67%	98%	36%
2011	26%	25%	9%	10%	5%	18%	5%	7%	17%	34%	15%
2012	30%	30%	14%	13%	11%	29%	21%	22%	29%	38%	3%
Average Return	28.33%	27.42%	21.92%	22.46%	21.91%	28.09%	25.12%	25.41%	27.97%	32.77%	8.31%
Std (σ)	27.07%	27.15%	31.24%	31.46%	28.60%	28.23%	33.09%	31.67%	27.81%	31.08%	17.29%
Efficiency (R/σ)	1.05	1.01	0.70	0.71	0.77	0.99	0.76	0.80	1.01	1.05	0.48
# negative years	4	4	4	5	5	4	4	4	4	4	5
# positive years	18	18	18	17	17	18	18	18	18	18	17
Best year	86%	85%	70%	68%	77%	81%	83%	80%	81%	98%	39%
Worst year	-20%	-21%	-47%	-46%	-40%	-28%	-53%	-47%	-24%	-30%	-37%

Notes: The table documents one-year returns obtained by investing in equally weighted buy-and-hold portfolios that select the most undervalued stock: the top decile of banks that each year at the end of April exhibit the largest positive valuation errors for a set of different multiple combinations. The portfolios are retained for the following year, and we compute the resulting annual returns. Each year this portfolio sorting is repeated until the last year of the time horizon under consideration. The portfolio is composed of U.S. bank stocks. No dividends are paid back to the investors. Returns are calculated over a one-year period starting four months after fiscal year-end, on April 30. Each column corresponds to a different screening strategy based on the valuation errors computed using the specific multiple combination indicated in the first row (for definitions of the metrics, see section 2.2). Portfolio returns are gross of transaction costs. The standard deviation of each portfolio and the efficiency ratio of each strategy are calculated as well.

Table 7

Investment strategies: long strategy on undervalued banks and shorting the market.

Year	P/BV & P/E (Basic, no Extra)	P/TBV & P/E (Basic, no Extra)	P/BV & P/E (FY2)	P/TBV & P/E (FY2)	P/Total Dividends & P/TBV	P/E (Basic, no Extra) & P/Customer Deposits	P/BV & P/Customer Deposits	P/Revenue & P/BV	P/E (Basic, no Extra) & P/Revenue	P/TBV & P/Revenue & P/Customer Deposits & P/E (Basic, no Extra)	S&P 500
1991	5%	5%	2%	9%	9%	7%	-1%	5%	7%	7%	13%
1992	29%	25%	44%	51%	43%	34%	68%	55%	39%	55%	11%
1993	32%	32%	52%	52%	29%	36%	48%	53%	36%	53%	6%
1994	25%	25%	9%	9%	26%	26%	24%	24%	25%	24%	2%
1995	7%	9%	2%	5%	2%	6%	4%	6%	7%	5%	14%
1996	17%	16%	19%	20%	15%	19%	15%	14%	16%	17%	27%
1997	30%	28%	27%	22%	24%	28%	26%	26%	28%	26%	22%
1998	40%	40%	25%	22%	31%	35%	38%	35%	36%	32%	39%
1999	-36%	-39%	-43%	-46%	-38%	-39%	-39%	-40%	-36%	-38%	20%
2000	-14%	-14%	-15%	-15%	-20%	-14%	-12%	-14%	-16%	-12%	9%
2001	53%	52%	59%	60%	44%	51%	50%	52%	51%	54%	-14%
2002	51%	53%	48%	46%	50%	61%	52%	51%	55%	57%	-14%
2003	62%	59%	43%	48%	57%	62%	60%	57%	63%	63%	-15%
2004	32%	28%	32%	36%	9%	38%	37%	41%	34%	37%	21%
2005	12%	12%	12%	13%	3%	14%	13%	11%	12%	17%	4%
2006	22%	21%	10%	11%	6%	19%	14%	17%	19%	26%	13%
2007	-6%	-8%	-12%	-14%	-15%	-6%	-10%	-10%	-5%	-5%	13%
2008	-9%	-11%	-28%	-27%	-7%	-10%	-21%	-20%	-12%	-2%	-7%
2009	18%	17%	-9%	-8%	-2%	10%	-14%	-8%	14%	8%	-37%
2010	27%	27%	13%	8%	28%	23%	5%	6%	26%	56%	36%
2011	15%	14%	-2%	-2%	-7%	7%	-6%	-4%	6%	22%	15%
2012	26%	26%	10%	9%	7%	25%	17%	18%	25%	34%	3%
Average Return	20%	19%	14%	14%	14%	20%	17%	17%	20%	24%	8.31%
Std (σ)	23%	23%	26%	27%	24%	24%	28%	27%	24%	26%	17.29%
Efficiency (R/σ)	0.87	0.82	0.52	0.52	0.56	0.81	0.59	0.63	0.82	0.93	0.48
# negative years	4	4	6	6	6	4	7	6	4	4	5
# positive years	18	18	16	16	16	18	15	16	18	18	17
Best year	62%	59%	59%	60%	57%	62%	68%	57%	63%	63%	39%
Worst year	-36%	-39%	-43%	-46%	-38%	-39%	-39%	-40%	-36%	-38%	-37%

Notes: The table documents one-year returns obtained by investing half of the portfolio in buy-and-hold equally weighted undervalued stocks (i.e., the top decile of banks that each year at the end of April exhibit the largest positive valuation errors for a set of different multiple combinations), and short selling the market index for the remaining half of the portfolio. The equally weighted portfolios are retained for the following year, and we compute the resulting annual returns. Each year this portfolio sorting is repeated until the last year of the time horizon under consideration. The portfolio is composed of U.S. bank stocks only. No dividends are paid back to the investors. Returns are calculated over a one-year period starting four months after fiscal year-end, on April 30. Each column corresponds to a different screening strategy based on the valuation errors computed using the specific multiple combination indicated in the first row (for definitions of the metrics, see section 2.2). Portfolio returns are gross of transaction costs. The standard deviation of each portfolio and the efficiency ratio of each strategy are displayed as well.

Table 8

Investment strategies: long-short strategy on undervalued and overvalued banks.

Year	P/BV & P/E (Basic, no Extra)	P/TBV & P/E (Basic, no Extra)	P/BV & P/E (FY2)	P/TBV & P/E (FY2)	P/Total Dividends & P/TBV	P/E (Basic, no Extra) & P/Customer Deposits	P/BV & P/Customer Deposits	P/Revenue & P/BV	P/E (Basic, no Extra) & P/Revenue	P/TBV & P/Revenue & P/Customer Deposits & P/E (Basic, no Extra)	S&P 500
1991	25%	24%	22%	29%	38%	18%	16%	22%	29%	23%	13%
1992	-1%	-5%	35%	38%	40%	9%	46%	37%	16%	31%	11%
1993	18%	26%	43%	43%	10%	28%	43%	45%	21%	46%	6%
1994	13%	14%	17%	16%	28%	21%	22%	25%	21%	22%	2%
1995	18%	20%	12%	15%	3%	17%	12%	14%	18%	12%	14%
1996	17%	14%	19%	23%	13%	23%	15%	15%	18%	21%	27%
1997	19%	17%	28%	25%	11%	14%	15%	13%	14%	12%	22%
1998	30%	29%	11%	9%	19%	28%	24%	22%	28%	20%	39%
1999	9%	5%	-51%	-57%	0%	4%	-6%	-1%	7%	7%	20%
2000	23%	24%	19%	19%	14%	22%	23%	20%	19%	23%	9%
2001	29%	27%	32%	33%	3%	25%	26%	28%	28%	28%	-14%
2002	25%	25%	29%	27%	20%	37%	25%	24%	31%	33%	-14%
2003	40%	37%	40%	44%	33%	39%	41%	38%	40%	33%	-15%
2004	33%	28%	34%	40%	10%	36%	38%	44%	36%	29%	21%
2005	14%	16%	12%	17%	7%	17%	19%	16%	14%	19%	4%
2006	26%	28%	3%	-1%	5%	24%	20%	21%	24%	26%	13%
2007	6%	4%	1%	-2%	-1%	6%	1%	2%	8%	9%	13%
2008	21%	20%	0%	4%	23%	17%	8%	7%	14%	31%	-7%
2009	18%	19%	-2%	-3%	16%	2%	-2%	4%	6%	19%	-37%
2010	70%	71%	76%	68%	89%	67%	73%	77%	64%	97%	36%
2011	36%	37%	21%	21%	32%	28%	34%	36%	26%	36%	15%
2012	37%	37%	14%	12%	19%	35%	28%	32%	36%	38%	3%
Average Return	23.96%	23.51%	18.91%	19.08%	19.59%	23.50%	23.70%	24.53%	23.42%	27.94%	8.31%
Std (σ)	14.48%	15.10%	23.57%	24.34%	19.50%	14.30%	17.86%	17.49%	13.05%	18.23%	17.29%
Efficiency (R/σ)	1.65	1.56	0.80	0.78	1.00	1.64	1.33	1.40	1.79	1.53	0.48
# negative years	1	1	2	4	2	0	2	1	0	0	5
# positive years	21	21	20	18	20	22	20	21	22	22	17
Best year	70%	71%	76%	68%	89%	67%	73%	77%	64%	97%	39%
Worst year	-1%	-5%	-51%	-57%	-1%	2%	-6%	-1%	6%	7%	-37%

Notes: The table documents one-year returns obtained by investing half of the portfolio in undervalued stocks (i.e., the top decile of banks that each year at the end of April exhibit the largest positive valuation errors for a set of different multiple combinations), and short selling overvalued banks (the bottom decile) for the remaining half of the portfolio. The equally weighted portfolios are retained for the following year, and we compute the resulting annual returns. Each year this portfolio sorting is repeated until the last year of the time horizon under consideration. The portfolio is composed of U.S. bank stocks only. No dividends are paid back to the investors. Returns are calculated over a one-year period starting four months after fiscal year-end, on April 30. Each column corresponds to a different screening strategy based on the valuation errors computed using the specific multiple combination indicated in the first row (for definitions of the metrics, see section 2.2). Portfolio returns are gross of transaction costs. The standard deviation of each portfolio and the efficiency ratio of each strategy have been displayed as well.

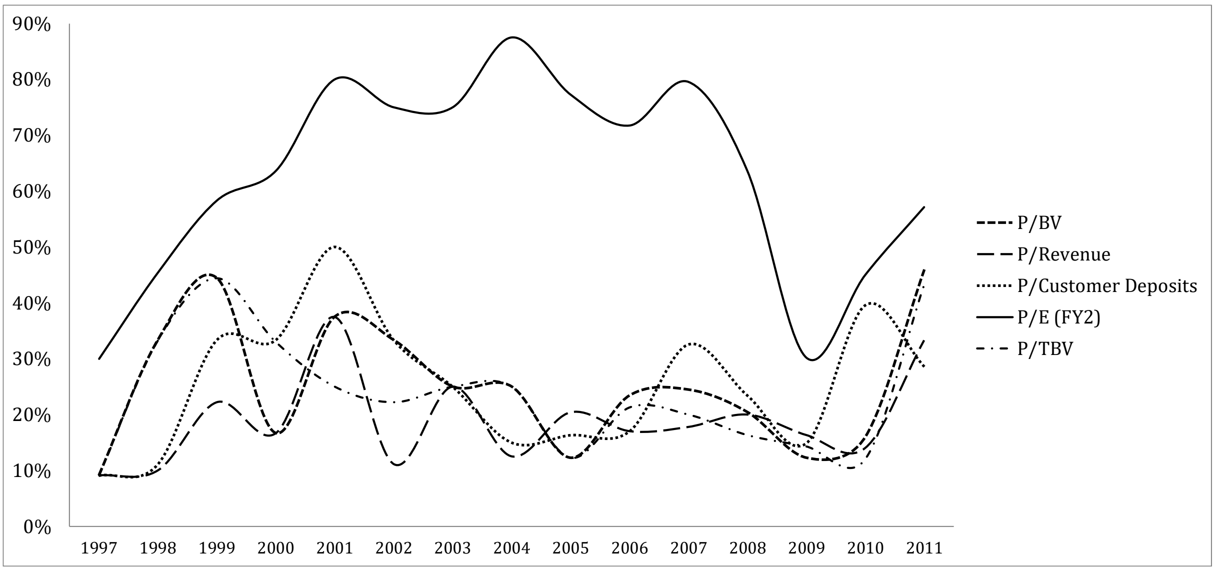

Fig. 1. Bank multiple accuracy performance across time: large European commercial sample.

The Y-axis represents the percentage of firms valued within 25% of their actual price. Errors are taken in absolute value. We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure and multiplying it by each relevant value driver.
P/E (FY2) is defined as share price divided by 2-year analysts' earnings forecast; P/BV is calculated as price divided by Compustat book value. See section 2.2 for complete definitions of the metrics.

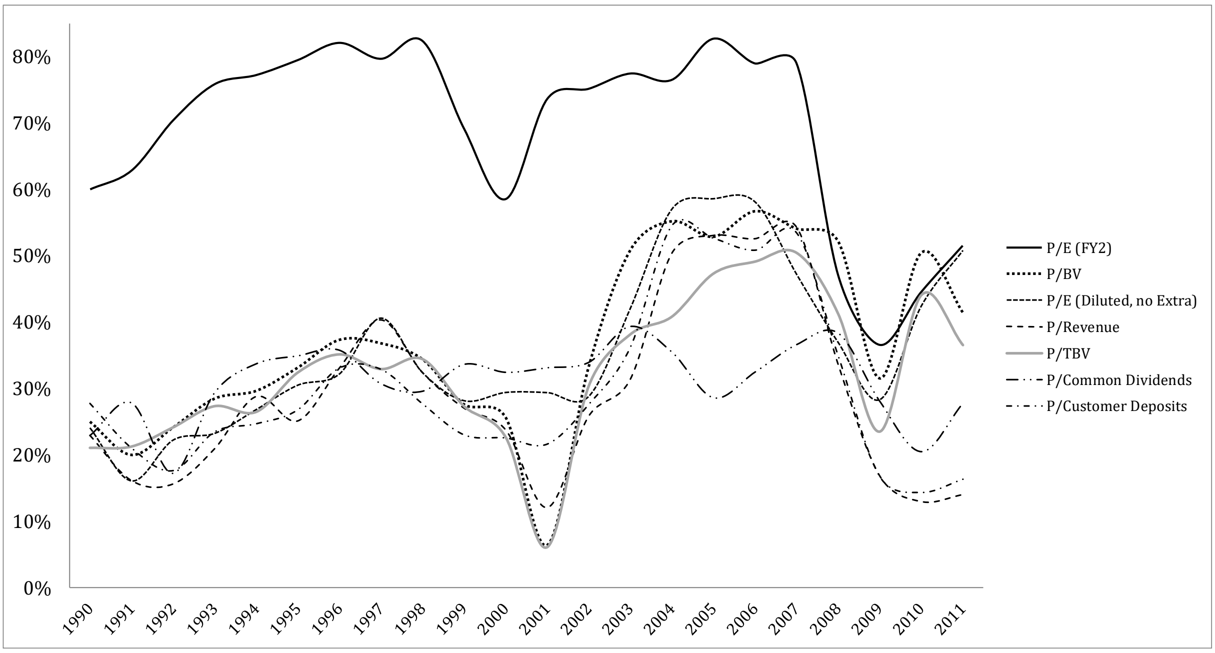

Fig. 2. Bank multiple accuracy performance across time: large U.S. commercial sample.

The Y-axis represents the percentage of firms valued within 25% of their actual price. Errors are taken in absolute value. We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure and multiplying it by each relevant value driver. See section 2.2 for complete definitions of the metrics.

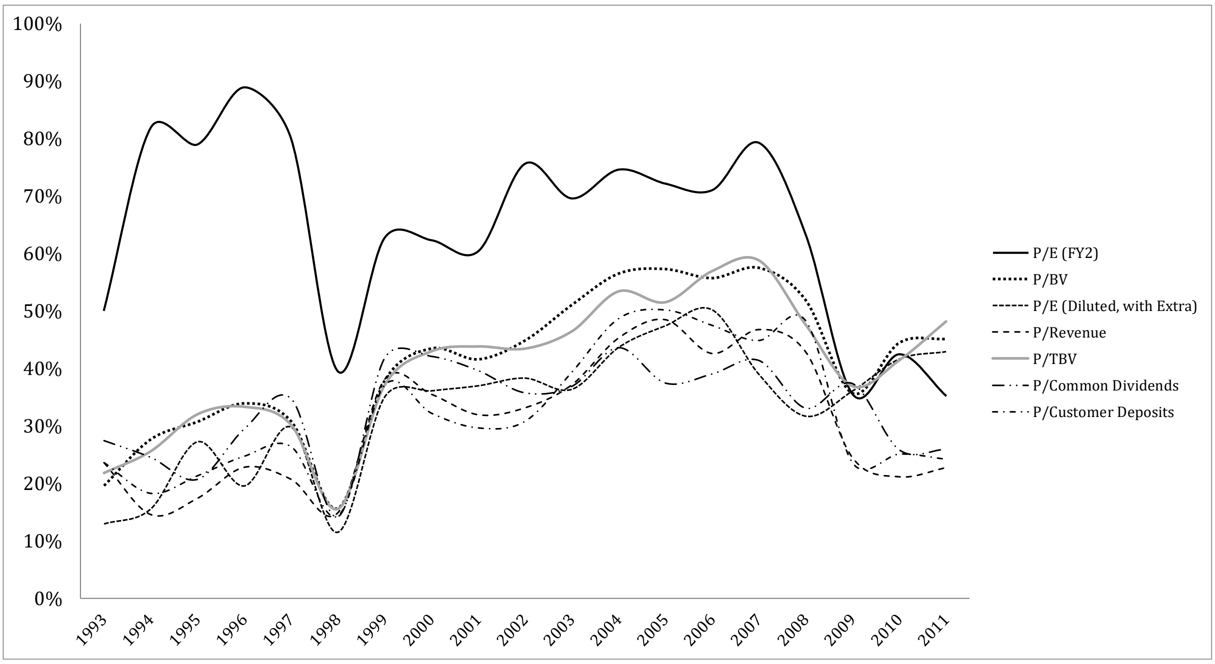

Fig. 3. Bank multiple accuracy performance across time: small U.S. commercial sample.

The Y-axis represents the percentage of firms valued within 25% of their actual price. Errors are taken in absolute value. We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure and multiplying it by each relevant value driver. See section 2.2 for complete definitions of the metrics.

Appendix

Appendix 1

Summary statistics of banking multiples: regional and business-size breakdown.

		P/E (FY1)	P/E (FY2)	P/Common Dividends	P/Total Dividends	P/BV	P/TBV	P/Revenue	P/Bank Deposits	P/Customer Deposits	P/E (Diluted, with Extra)	P/E (Diluted, no Extra)	P/E (Basic, with Extra)	P/E (Basic, no Extra)
EU IB	**Median**	13.05x	11.53x	28.42x	29.08x	1.66x	1.31x	1.31x	0.29x	0.16x	NA	NA	14.46x	14.54x
	95 Pct.	35.14x	31.68x	91.40x	124.06x	5.98x	8.35x	8.35x	61.41x	18.70x	NA	NA	71.66x	72.12x
	75 Pct.	20.60x	15.54x	45.45x	46.19x	2.70x	2.99x	2.99x	1.16x	0.39x	NA	NA	24.41x	24.77x
	25 Pct.	9.53x	7.87x	18.80x	19.43x	1.01x	0.78x	0.78x	0.13x	0.09x	NA	NA	8.21x	8.51x
EU CB Large	**Median**	13.36x	11.97x	27.86x	29.11x	1.37x	1.02x	1.02x	0.51x	0.12x	NA	NA	12.43x	13.25x
	95 Pct.	34.67x	27.05x	132.08x	188.10x	10.20x	3.67x	3.67x	5.18x	1.47x	NA	NA	70.59x	90.18x
	75 Pct.	19.35x	15.48x	43.50x	46.06x	2.38x	1.75x	1.75x	1.05x	0.23x	NA	NA	18.12x	18.84x
	25 Pct.	9.50x	8.17x	18.83x	19.01x	0.76x	0.47x	0.47x	0.19x	0.07x	NA	NA	8.83x	9.16x
EU CB Small	**Median**	14.80x	13.47x	19.98x	20.01x	1.09x	1.03x	1.03x	0.55x	0.10x	NA	NA	12.77x	12.77x
	95 Pct.	44.11x	42.60x	83.81x	85.02x	4.18x	4.11x	4.11x	5.43x	0.87x	NA	NA	50.31x	54.78x
	75 Pct.	21.55x	21.11x	36.03x	36.27x	1.84x	1.85x	1.85x	1.40x	0.19x	NA	NA	20.10x	20.10x
	25 Pct.	9.88x	9.19x	9.80x	9.55x	0.36x	0.36x	0.36x	0.15x	0.05x	NA	NA	8.18x	8.18x
US IB	**Median**	14.46x	13.11x	39.64x	36.91x	1.33x	1.44x	1.44x	NA	0.14x	11.37x	11.38x	11.16x	11.24x
	95 Pct.	33.93x	28.67x	243.03x	242.50x	5.15x	4.92x	4.92x	NA	0.52x	65.39x	61.08x	64.83x	58.78x
	75 Pct.	19.57x	17.47x	70.43x	66.21x	2.15x	2.52x	2.52x	NA	0.25x	17.85x	17.85x	17.57x	17.57x
	25 Pct.	11.34x	9.74x	22.03x	20.90x	0.58x	0.67x	0.67x	NA	0.06x	5.58x	5.58x	5.32x	5.32x
US CB Large	**Median**	14.12x	12.85x	30.48x	29.53x	1.42x	1.62x	1.62x	NA	0.15x	12.19x	12.21x	12.01x	12.02x
	95 Pct.	30.79x	24.88x	287.21x	273.03x	7.00x	7.35x	7.35x	NA	0.66x	75.54x	75.12x	74.10x	73.70x
	75 Pct.	17.43x	15.61x	50.88x	48.72x	2.23x	2.49x	2.49x	NA	0.22x	17.25x	17.27x	17.03x	17.05x
	25 Pct.	11.25x	10.36x	18.41x	17.78x	0.77x	0.77x	0.77x	NA	0.07x	6.17x	6.18x	6.08x	6.10x
US CB Small	**Median**	14.06x	12.57x	32.65x	31.50x	1.12x	1.43x	1.43x	NA	0.13x	12.65x	12.66x	12.41x	12.43x
	95 Pct.	36.76x	28.84x	205.84x	234.41x	3.12x	4.77x	4.77x	NA	0.42x	69.79x	69.24x	67.54x	67.37x
	75 Pct.	18.04x	15.69x	52.90x	50.66x	1.62x	2.20x	2.20x	NA	0.19x	18.59x	18.60x	18.29x	18.32x
	25 Pct.	11.14x	9.97x	22.34x	21.31x	0.74x	0.87x	0.87x	NA	0.08x	8.19x	8.25x	8.03x	8.08x

Notes: Banks subsamples are based on size (small or large), business segment (investment [IB] or commercial [CB]), and region (the eurozone [EU] or the United States [US]). Sample banks are collected in April each year between 1990 and 2012. We require nonmissing values for a set of core financial and accounting variables from Compustat, and nonmissing 1-year and 2-years analysts' earnings forecasts from I/B/E/S. P/E (FY1) and P/E (FY2) are defined as share price divided by 1-year and 2-years I/B/E/S analysts' earnings forecasts, respectively; P/BV is the price divided by the book value of equity; P/revenue is calculated as the price divided by the bank's total revenues. NA indicates that a multiple is not available. See section 2.2 for complete definitions of the metrics.

Appendix 2

Valuation errors descriptive statistics: bias, MAD, and MSE.

		P/E (FY1)	P/E (FY2)	P/Common Dividends	P/Total Dividends	P/BV	P/TBV	P/Revenue	P/Bank Deposits	P/Customer Deposits	P/E (Diluted, with Extra)	P/E (Diluted, no Extra)	P/E (Basic, with Extra)	P/E (Basic, no Extra)
EU IB	Bias	0.041	0.026	0.189	0.187	0.070	0.074	0.144	0.502	6.938	NA	NA	0.138	0.081
	MAD	0.509	0.428	0.697	0.714	0.613	0.676	0.788	1.377	7.390	NA	NA	0.780	0.698
	MSE	0.257	0.187	0.362	0.382	0.277	0.349	0.648	1.053	139.949	NA	NA	0.624	0.518
EU CB Large	Bias	0.015	0.013	0.124	0.117	0.096	0.111	0.080	0.354	0.093	NA	NA	0.088	0.089
	MAD	0.352	0.307	0.737	0.759	0.804	0.867	0.769	1.291	0.759	NA	NA	0.551	0.568
	MSE	0.152	0.111	0.639	0.643	0.814	1069	0.738	2.706	0.675	NA	NA	0.344	0.382
EU CB Small	Bias	0.052	0.080	0.050	0.100	0.180	0.187	0.201	0.379	0.226	NA	NA	0.214	0.214
	MAD	0.434	0.433	0.858	0.922	1.305	1.330	1.198	1.460	1.267	NA	NA	1.247	1.247
	MSE	0.231	0.211	0.750	0.792	2042	2.150	1.037	3.281	1.629	NA	NA	0.595	0.595
US IB	Bias	0.022	0.020	0.054	0.064	0.039	0.041	0.046	NA	0.042	0.050	0.050	0.051	0.051
	MAD	0.353	0.358	0.604	0.646	0.515	0.561	0.579	NA	0.574	0.572	0.572	0.581	0.581
	MSE	0.152	0.158	0.462	0.517	0.319	0.385	0.435	NA	0.468	0.343	0.344	0.347	0.352
US CB Large	Bias	0.002	0.002	0.003	0.005	0.063	0.074	0.027	NA	0.006	0.005	0.006	0.005	0.006
	MAD	0.269	0.256	0.503	0.516	0.566	0.609	0.626	NA	0.565	0.489	0.489	0.491	0.490
	MSE	0.095	0.081	0.305	0.302	0.258	0.286	0.299	NA	0.316	0.260	0.259	0.261	0.259
US CB Small	Bias	0.004	0.004	0.014	0.017	0.002	0.002	0.004	NA	0.003	0.004	0.004	0.004	0.004
	MAD	0.284	0.276	0.496	0.512	0.372	0.382	0.477	NA	0.468	0.469	0.466	0.472	0.470
	MSE	0.118	0.105	0.281	0.291	0.194	0.203	0.285	NA	0.284	0.278	0.275	0.280	0.279

Notes: For the method of computing valuation errors, see section 4.2. Bank subsamples are based on size (small or large), business segment (investment [IB] or commercial [CB]), and region (the eurozone [EU] or the United States [US]). We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure based on geographical and business-size characteristics, and multiplying it by each relevant value driver. Sample banks are collected in April each year between 1990 and 2012. We require nonmissing values for a set of core financial and accounting variables from Compustat, nonmissing share price from Bloomberg, and nonmissing 1-year and 2-years analysts' earnings forecasts from I/B/E/S. NA indicates that a multiple is not available. The table focuses on bias, mean absolute deviation (MAD), and mean-squared error (MSE); see equations 2,3, and 4 in section 4.2 for complete definitions of the statistics employed.

Appendix 3

Distribution of valuation errors: U.S. and European bank subsamples.

		Obs.	Bias	5%	25%	Median	75%	95%			Obs.	Bias	5%	25%	Median	75%	95%
EU IB	P/E (FY1)	127	0.041	-0.715	-0.455	-0.136	0.296	1.119	US IB	P/E (FY1)	279	0.022	-0.612	-0.286	-0.048	0.215	0.740
	P/E (FY2)	130	0.026	-0.638	-0.388	-0.114	0.272	0.890		P/E (FY2)	287	0.020	-0.576	-0.279	-0.096	0.261	0.721
	P/Common Dividends	114	0.189	-0.791	-0.499	-0.134	0.275	1.336		P/Common Dividends	316	0.054	-0.891	-0.506	-0.169	0.391	1.538
	P/Total Dividends	117	0.187	-0.797	-0.517	-0.100	0.287	1.333		P/Total Dividends	322	0.064	-0.892	-0.517	-0.196	0.414	1.772
	P/BV	186	0.070	-0.757	-0.525	-0.179	0.305	0.985		P/BV	312	0.039	-0.741	-0.425	-0.156	0.282	1.311
	P/TBV	179	0.074	-0.812	-0.570	-0.226	0.332	1.121		P/TBV	312	0.041	-0.776	-0.468	-0.198	0.377	1.438
	P/Revenue	184	0.144	-0.902	-0.632	-0.251	0.361	2.094		P/Revenue	364	0.046	-0.814	-0.491	-0.165	0.236	1.645
	P/Banks Deposits	33	0.502	-0.995	-0.773	-0.560	0.305	2.257		P/Customer Deposits	305	0.042	-0.737	-0.490	-0.226	0.365	1.767
	P/Customer Deposits	80	6.938	-0.972	-0.517	1.089	6.151	35.589		P/E (Diluted, with Extra)	346	0.050	-0.854	-0.463	-0.177	0.330	1.234
	P/E (Basic, with Extra)	152	0.138	-0.841	-0.623	-0.249	0.279	2.225		P/E (Diluted, no Extra)	346	0.050	-0.842	-0.467	-0.168	0.305	1.231
	P/E (Basic, no Extra)	148	0.081	-0.839	-0.601	-0.210	0.285	1.810		P/E (Basic, with Extra)	346	0.051	-0.856	-0.470	-0.185	0.341	1.223
EU CB Large	P/E (FY1)	448	0.015	-0.641	-0.298	-0.050	0.205	0.766	US CB Large	P/E (FY1)	3,26	0.002	-0.539	-0.212	-0.049	0.113	0.583
	P/E (FY2)	457	0.013	-0.603	-0.239	-0.046	0.177	0.618		P/E (FY2)	3,315	0.002	-0.483	-0.196	-0.056	0.095	0.556
	P/Common Dividends	251	0.124	-0.913	-0.545	-0.207	0.244	2.017		P/Common Dividends	3,582	0.003	-0.896	-0.460	-0.086	0.345	1.137
	P/Total Dividends	274	0.117	-0.943	-0.594	-0.215	0.199	2.070		P/Total Dividends	3,746	0.005	-0.897	-0.463	-0.110	0.301	1.159
	P/BV	436	0.096	-0.902	-0.578	-0.366	0.089	2.650		P/BV	4,184	0.063	-0.855	-0.434	-0.152	0.170	1.137
	P/TBV	436	0.111	-0.912	-0.622	-0.404	0.089	3.322		P/TBV	4,124	0.074	-0.865	-0.465	-0.182	0.190	1.178
	P/Revenue	439	0.080	-0.862	-0.603	-0.366	0.261	2.235		P/Revenue	4,091	0.027	-0.840	-0.529	-0.247	0.129	1.249
	P/Banks Deposits	208	0.354	-1.000	-0.808	-0.513	0.026	5.684		P/Customer Deposits	4,129	0.006	-0.833	-0.496	-0.217	0.168	1.370
	P/Customer Deposits	426	0.093	-0.922	-0.599	-0.290	0.275	2.059		P/E (Diluted, with Extra)	3,737	0.005	-0.864	-0.429	-0.113	0.212	1.140
	P/E (Basic, with Extra)	279	0.088	-0.854	-0.394	-0.085	0.265	1.376		P/E (Diluted, no Extra)	3,733	0.006	-0.862	-0.428	-0.114	0.210	1.139
	P/E (Basic, no Extra)	278	0.089	-0.856	-0.408	-0.106	0.301	1.502		P/E (Basic, with Extra)	3,746	0.005	-0.863	-0.432	-0.116	0.209	1.153
EU CB Small	P/E (FY1)	180	0.052	-0.691	-0.366	-0.009	0.319	0.895	US CB Small	P/E (FY1)	1,07	0.004	-0.613	-0.215	-0.021	0.166	0.621
	P/E (FY2)	170	0.080	-0.690	-0.332	0.020	0.257	0.870		P/E (FY2)	991	0.004	-0.557	-0.217	-0.027	0.142	0.593
	P/Common Dividends	235	0.050	-0.978	-0.722	-0.377	0.304	1.992		P/Common Dividends	2,564	0.014	-0.850	-0.437	-0.095	0.266	1.037
	P/Total Dividends	240	0.100	-0.977	-0.738	-0.386	0.294	1.961		P/Total Dividends	2,723	0.017	-0.877	-0.454	-0.100	0.258	1.095
	P/BV	372	0.180	-0.936	-0.856	-0.733	0.002	4.021		P/BV	3,35	0.002	-0.667	-0.314	-0.083	0.208	0.967
	P/TBV	372	0.187	-0.946	-0.863	-0.754	0.011	4.078		P/TBV	3,318	0.002	-0.685	-0.330	-0.088	0.215	1.010
	P/Revenue	372	0.201	-0.906	-0.806	-0.636	0.130	2.486		P/Revenue	3,342	0.004	-0.764	-0.421	-0.144	0.243	1.202
	P/Banks Deposits	105	0.379	-0.984	-0.939	-0.675	0.758	4.492		P/Customer Deposits	3,324	0.003	-0.764	-0.416	-0.131	0.244	1.225
	P/Customer Deposits	359	0.226	-0.952	-0.818	-0.641	-0.109	3.548		P/E (Diluted, with Extra)	2,965	0.004	-0.826	-0.415	-0.106	0.244	1.165
	P/E (Basic, with Extra)	233	0.214	-0.963	-0.831	-0.625	-0.165	1.372		P/E (Diluted, no Extra)	2,963	0.004	-0.823	-0.414	-0.104	0.250	1.142
	P/E (Basic, no Extra)	233	0.214	-0.963	-0.831	-0.624	-0.155	1.391		P/E (Basic, with Extra)	2,965	0.004	-0.823	-0.419	-0.109	0.245	1.163

Notes: For the method of computing valuation errors, see section 4.2. Bank subsamples are based on size (small or large), business segment (investment [IB] or commercial [CB]), and region (the eurozone [EU] or the United States [US]). We compute errors as the difference between the inferred price and the actual price of the stock at the end of April, divided by the actual price. We estimate the inferred price with an out-of-sample approach, calculating for each multiple a peer-group measure based on geographical and business-size characteristics, and multiplying it by each relevant value driver. Sample banks are collected in April each year between 1990 and 2012. We require nonmissing values for a set of core financial and accounting variables from Compustat, nonmissing share price from Bloomberg, and nonmissing 1-year and 2-years analysts' earnings forecasts from I/B/E/S.

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