Testing for Experience Effects in Banking

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Abstract

This paper tests for empirical evidence of learning by doing in banking with the aim of identifying a micro-founded driver of financial sector development. Learning by doing entails cumulative experience reducing the amount of labor or other inputs required to produce the same amount of output. However identifying this experience effect poses challenges because firms may increase output as input prices decline, introducing the possibility of endogeneity bias in estimating the cost function. Applying a two-step correction procedure to my bank cost function, I correct for endogeneity as well as selection biases arising from sample dependence. The problem of these biases has not been addressed in empirical work on learning by doing, or the banking efficiency literature, nor have experience effects been focused on in the banking context. Using the corrected model, results suggest that experience is associated with reduced costs: the experience effect is decreasing and fades after around 10 years. For example, on average, a 10 percent increase in experience, for a bank of around 1 year of age is associated with a 10.9 percent decline in variable cost; for a 5 year old bank, that becomes a 2 percent decline in variable cost.

Keywords: financial development, learning by doing, banking efficiency
JEL codes: G2, D830

1 Introduction

This paper attempts to find micro foundations for financial sector development. Using the firm-level perspective, the paper is focused on financial intermediaries and the cost of producing credit. In this framework, a well-developed financial sector operates with lower financial intermediation costs.[1] How does this come about? What leads to a financial intermediary becoming more efficient in producing credit and allocating capital? This paper hypothesizes that a learning by doing mechanism improves banking cost efficiency, and draws on the banking efficiency literature to test this hypothesis.[2]

From the macroeconomic perspective, a broad literature investigates the financial sector and its relation to growth. Financial sector development facilitates welfare enhancing interactions between savers and entrepreneurs, reducing the costs of asymmetric information between lenders and borrowers. Access to capital for entrepreneurs allows financially constrained agents to borrow, invest and go forward with economically viable projects. Efficient allocation of capital ensures correctly priced funding for those projects with the best expected outcome. An effective financial sector can channel the proceeds from the entrepreneurial activities to households, resulting in welfare gains for the overall economy. It is therefore important to understand the factors and mechanisms that facilitate the development of an efficient financial sector.

Institutional and political characteristics, as well as economic openness have been put forward as important factors driving financial sector development. Levine et al. (2000) establishes that laws that strengthen creditors' rights, contract enforcement and accounting practices facilitate financial development. In LaPorta et al. (2008), the authors argue that capital market development depends on institutional quality and regulatory conditions, which are related to the origins of a country's legal system. Rajan and Zingales (2003) focuses on political economy issues making the case that domestic incumbents oppose financial development, and, that this incumbent opposition can be overcome by allowing cross-border trade and capital flows. Baltagi et al. (2009) empirically validates that closed economies can spur banking sector development in their economy by opening up, and Chinn and Ito (2005) caveats this by arguing that a poor legal and institutional environment will eliminate the capital-account openness effect on financial development.

In the banking literature, both economies of scope and scale have been theorized as sources of banking efficiency. Financial intermediation models predict economies of

[1] Typically in the macro literature, financial development is measured by financial depth and breadth, eg. as private credit to GDP and stockmarket value to GDP.

[2] It is not obvious to what degree banks would pass on cost savings to users of financial intermediation services given regulatory heterogeneity and competitive factors. As such, this paper looks at reductions in self-reported production costs to test for experience effects.

scale in the presence of fixed financial transaction costs, portfolio diversification, or a fractional reserves banking set up.[3] A literature on banking efficiency[4] estimates X-efficiency and tests for empirical evidence of economies of scale in banking. Hughes and Mester (1993, 1998, 2011) taking a structural approach, found scale economies are evident for all size banks when risk (asset quality) is incorporated into the bank production technology. This result alone would imply that larger banks, no matter whether from mergers, acquisitions or organic growth, would all have lower unit costs than smaller banks.

But, perhaps bank efficiency is influenced by experience, as distinct from scale.[5] Perhaps the history of a bank's operational activities makes a difference. It may be the case that as banks grow larger they gain experience from building their asset portfolio and managing their liabilities, and that experience leads to improvements. Learning from production could lead to successful process innovations or organizational improvements, which in turn could lead to more production which yields more learning, suggesting a cycle of learning and innovation.[6]

For example, given the classic scale economy example of one ideal loan contract being similarly costly to use for 1 borrower as for 1,000, what explains how this optimal loan contract came to be produced? A bank's team of lawyers do not write an entirely new contract for every loan, somehow an ideal template contract is developed. Perhaps the first loan contract worked well, but the experience motivated a few changes in the covenants and authorization process. With these improvements, the second loan contract required fewer labor hours and achieved a similar result. The next was improved further, until a standardized loan contract could be implemented with a predictable and efficient level of labor input. The standard loan contract is scaleable. In this way, learning precedes gains from scale; and these effects are distinct. Experience involves learning with each unit produced and thus sequential improvements. And, unlike scale effects, gains from experience are not reversed when output is reduced.

For firms in general, investment in research and development, innovation, and experience have all been shown to drive productivity. The effects of experience or learning by doing in particular, has been modeled and studied since the mid 1930s. Arrow (1962) developed a theoretical model with learning embodied in successive vintages of capital motivated by empirical studies of ship building and other industrial manufacturing processes. For example, Wright (1936) documented a learning curve in the manufacture

[3]For an overview and textbook treatment of these banking models, see Freixas and Rochet (2008).

[4]For a survey, please see Hughes and Mester (2010).

[5]Hunter and Timme (1986) find that *ceteris paribus*, banks with greater output realized more technological change over the period studied.

[6]Homma et al. (2014) although focused on market structure mechanisms, find that more efficient banks grow larger.

of air frames and other researchers subsequently found evidence of this learning-by-doing relationship in a range of industries (for a survey see Ghemawat (1985)). More recently, Bahk and Gort (1993), Barrios and Strobl (2004) analyzed data on manufacturing plants and Irwin and Klenow (1994) examined the semiconductor industry for firm-specific learning by doing and knowledge spillovers to the sector as a whole and the global semiconductor industry.[7]

This paper hypothesizes that banks may improve over time, and in particular that experience creating credit can reduce the cost of producing it. The focus will be on firm-specific learning: a firm's cost to produce one unit of output declines as the firm accumulates production experience, given production technology and firm size. The goal is to identify whether this dynamic occurs in banking. In research related to this question,DeYoung and Hasan (1998) does find that new banks have a profitability curve: start up banks in the 1990s on average took nine years to become as profitable as an established bank, with more than half of the gains made during the first three years of operation. The authors do not explicitly discuss or test for experience effects, however their results would fit with the hypothesis that a learning curve exists in banking.

This paper first shows, using US bank data, that initial estimation results on a crossection of banks gave no evidence of experience decreasing costs. However using the DeYoung and Hasan (1998) result to split the sample by age, experience was associated with reduced costs for the under nine years of age subsample of banks. Adjusting the model to account for this, experience was associated with lower cost for banks up to around 2 years of age. However, a key concern with banking efficiency studies as well as cost function estimation is the difficulty with dealing with endogeneity issues and sample dependence. Applying a two-step correction procedure to the bank cost function, this paper explicitly corrects for endogeneity as well as selection biases. The corrected model implies this experience effect continues up to around 10 years of age, about 5 times as long as estimated by the uncorrected model. For example, on average, a 10 percent increase in experience, for a bank of around 1 year of age is associated with a 10.9 percent decline in variable cost; for a 5 year old bank, that becomes a 2 percent decline in variable cost.

The rest of the paper proceeds as follows: the next section develops a bank-specific production and cost function incorporating learning by doing. Section three discusses the econometric issues and approach to testing for experience effects in banking and reports the econometric results. Section four concludes and discusses implications of evidence of a learning curve in banking.

[7] Empirical studies of learning by doing in manufacturing identify firm-specific learning, and sector-wide as well as international knowledge spillovers of various magnitudes using cumulative output (of the firm or of the national and global sectors) as a proxy for production experience.

2 Incorporating Experience into Banking

Much of the research on learning by doing uses industrial manufacturing production specifications with Cobb-Douglas functional forms. To analyze experience effects in banking, I extend this approach drawing on the banking efficiency literature to model banking activity. This yields the following description of bank technology as a transformation function $T(.)$ characterized by optimized production:

$$T(Q, X, K, RSK, EXP) = Q - f(Q, X, K, RSK, EXP) = 0 \tag{1}$$

where Q is the quantity of output, X is a vector of production inputs, RSK is a measure of asset quality, K is bank equity capital, and EXP is experience, the variable of interest. From this formulation a cost function is then derived.

2.1 Experience

The learning by doing literature explicitly considers firm-specific experience as well as local and global knowledge spillovers. This paper focuses in on the extent of firm-specific learning in banking, ie how a bank's own experience affects that financial intermediary's efficiency. Furthermore, the notion of experience is broad and crucially is not restricted to a lender-single borrower relationship. Experience in credit activities with *any* borrower is counted as experience. Several financial intermediary models address the issue of gains from experience with a particular counter-party. For example, Diamond (1991) shows in a simple 2-period model how a particular borrower can build a reputation by successfully repaying an initial loan. Relationship banking models involve the bank paying a one time sunk cost associated with monitoring with the first loan to a particular counter-party. Future loans to that particular borrower would not incur this cost.[8] These models imply counter-party specific cost-dynamics. I am looking at a different question: whether *all* credit creation experience can increase bank efficiency, reducing costs. With each transaction, the bank learns some new information and efficiency in collecting and effectively analyzing and using that information may rise.

For example, one theorized loan management cost involves *monitoring* activities to address the moral hazard problem. In Diamond (1984), banks arise to perform delegated monitoring. In Boot and Thakor (1997) a subset of firms with good reputations can go to the debt markets directly, but others require monitoring to obtain credit and thus need banks. The efficiency gains from experience could be reflected in a decline in the amount of monitoring labor required for the same volume of loans as the bank recognizes what information is crucial and sufficient for efficient monitoring. Similarly,

[8] See Freixas and Rochet (2008) page 99-100 for a simple example.

screening potential borrowers is theorized as a key function of financial intermediaries to address the adverse selection problem. One could expect this work to become less intensive as more effective screening technologies and characteristics of the applicant population are learned over time.

Or, one can think of a *cost of default* incurred by the bank when a portion of borrowers are unable to repay and the bank then must collect and liquidate assets.[9] Increased experience could lead to an increase in efficient foreclosure execution (or decrease in labor needed to process the same-sized default).[10]

The paper thus hypothesizes that increased experience of a general kind reduces the bank's cost to create credit. This conjecture parallels the learning by doing hypothesis that manufacturing production cost declines because on-the-job experience reduces the amount of labor or other inputs required to produce the same amount of output. Thus following the learning by doing literature, a measure of experience is included in the bank production (and cost function).

2.2 Asset quality and bank equity

Distinct from manufacturing production processes, the primary function of financial intermediaries is transforming assets, taking in short-term deposits and other borrowed funds and creating longer or more risky credit contracts. The quality of those loan contracts may affect the bank's cost of borrowing funds.[11] For example when a bank manager chooses to pursue higher expected revenue, both the payoff size and the probability of payoff can be targetted. The risk-return trade off can lead to riskier assets on the balance sheet. If the bank's creditors see this as a deterioration in the quality of the bank's asset portfolio, they may charge more to extend credit to that bank (or withdraw their deposits).[12] Because of this relation between output quality and input costs, the model for financial intermediary "production" should capture this distinct aspect of credit creation by including a risk term, RSK, in the production function. Also particular to finance, bank equity capital K can both substitute for borrowed funds and influence borrowing costs—a higher capital cushion suggests a safer bank,

[9] For example see Jappelli and Pagano (2005) in which the authors model repayment with recovery rates (less than one) for the firm's cash flow and the pledged collateral. Or, in Townsend (1979), verification of a borrower's revenues requires a fixed auditing cost. Bernanke et al. (1999) model this auditing cost as the cost incurred by the financial intermediary when the entrepreneur defaults.

[10] Bank experience could alternatively lead to a reduction in collateral requirements for the same loan, but this outcome reduces the borrower's "costs" and in this paper the focus is on the production costs of the bank.

[11] See Hughes and Mester (1998).

[12] A bank run, or counter-party risk, would be an extreme version of this dynamic, whereby a bank's lenders and depositors fear the bank's assets are of such poor quality they refuse to roll-over or extend new credit to that bank, and/or this precipitates a run on the bank. The experience of Lehman Brothers in the interbank market illustrates this dynamic unfolding in the shadow banking sector.

and can lead to lower rates demanded by creditors. Hence we need to include bank equity in the transformation function.

2.3 Inputs

A financial intermediary's inputs include physical capital and labor as is typical of other firm types. However a decision must be made on how to classify deposits, as inputs or as an indicator of financial services output.[13] Sealey and Lindley (1977) make the argument that for financial intermediaries, a distinction must be made between "technical" vs. "economic" production in order to classify inputs versus outputs. While a bank technically produces deposits, deposits are economic inputs to the production of credit. For a profit maximizing firm, the output must be of higher value than the input, when measured in market prices. Banks "pay" depositors both via servicing and paid interest, but primarily earn their revenue from assets. Thus applying a financial intermediation approach, deposits should be considered an input.

From this perspective, funding for a bank is a key production input, unlike in corporate finance theory for typical firms, where the firm's financing decisions are usually distinguished from production decisions. Deposits provide one relatively stable source of funding. In addition, other methods of bank borrowing provide other sources each with their own attributes and associated cost.[14]

2.4 Output

Unlike manufacturing, for which the learning-by-doing theory was developed, financial services suffer a peculiarity in that output is ill-defined.[15] A widget produced from a set of inputs, is clearly a unit of output and that unit when sold for a given price generates revenue for the manufacturing firm. It is straightforward to define current output (the widgets produced this year) versus cumulative output (the widgets produced up to the end of last year). Taking a financial intermediation approach, banks produce credit. As discussed in Sealey and Lindley (1977), the process of asset transformation yields "earning assets" which generate revenue streams for the bank based on the interest charged on those assets.[16] In banking, Q can be defined as earning assets. However note that, using this definition, a loan produced for example 2 years ago is likely to still

[13]See Holod and Lewis (2011) for a recent take on this dilemma.

[14]Banks can borrow in a variety of ways via Fed Funds and repo markets, or negotiable certificates of deposits for example.

[15]For an overview of different approaches to bank production function specifications, see Mlima and Hjalmarsson (2002).

[16]Banks also book income from fees and off-balance sheet activities. The latter can be important revenue generators for larger banks.

be providing revenue to the bank and is therefore measured as current output.[17]

2.5 The cost function

Total cost of producing output Q is the sum of the bank specific inputs times their prices,

$$C = W_p'X_p + W_d'X_d + W_kK \tag{2}$$

where X_d includes the finance specific inputs: deposits and other borrowed funds, and X_p represents the usual physical inputs: labor and physical capital. W_d contains the cost of deposits and other borrowing, and W_p is the vector of prices for labor and facilities. W_k is the cost of equity capital. In the short-run, one can treat equity as quasi-fixed and minimize costs conditional on the level of equity K to formulate a cash-flow variable cost function.

$$VC(Q, W_p, W_d, K, RSK, EXP) = min_{X_p,X_d}(W_p'X_p + W_d'X_d) \tag{3}$$

such that $T(Q, X, K, RSK, EXP) = 0$ and $K = K^0$.

Using a Cobb-Douglas formulation of the variable cost function, and taking logs, the variable cost function can be written as:

$$lnVC = \alpha + \beta_q lnQ + \sum_j \gamma_j lnW_j + \beta_k lnK + \beta_{rsk} lnRSK + \beta_{exp} lnEXP \tag{4}$$

This is the key estimation equation.

2.6 Variable definitions

Experience, EXP, in the manufacturing setting has been proxied by both cumulative output and age. For banks, distinguishing between cumulative output and current output is non-trivial. Consequently, modeling effects from cumulative output—a common measure of experience—poses issues. If banking cumulative output is defined as earning assets, this is a measure of size, which would then conflate experience and scale effects. I therefore restrict attention to using Age of the bank as the proxy for firm-specific experience. The Age variable is continuous in my dataset and calculated from the time the bank received its charter. A negative coefficient on the Age variable (costs are decreasing in experience) would support the hypothesis of learning by doing in banking.

[17]This issue is not unique to banks; service provision businesses may not define output as simply as manufacturers because of the duration of the contract and the revenue stream.

Non-performing loans and other non-performing assets on the bank's balance sheet are used to proxy risk. Although this is an *ex post* measure of asset quality, it nevertheless provides a metric of the risk associated with the banks assets. (See Table 1 for a summary of variable definitions.)

Table 1: Variable Definitions

VC	Variable Cost: the sum of reported salaries and benefits paid, rents, interest expenses, and bank funding costs.
Q	Output (*Earning Assets*): the total value of loans and other earning assets on the bank's balance sheet.
W_1	Price of labor: the sum of salaries and benefits paid, divided by number of employees.
W_2	Price for physical capital: average dollar value of premises and fixed assets.
W_3	Price for deposits: total interest paid on deposits divided by amount of deposits.
W_5	Price for other borrowed funds: total interest paid on other borrowed funds divided by amount of other borrowed funds.
K	Quantity of financial capital (*Equity*): sum of shareholders' equity, loan loss reserves, and subordinated debt
RSK	Asset quality measure (*Risk*): proxied by average total volume of non-performing and non-accruing loans (30 days or more past due) plus gross charge offs.[1]
EXP	Experience: proxied by *Age* of bank, from the date the charter was granted.

1. Gross charge offs are the amount the bank has written off for a given non-performing asset before accounting for any recovery value. Some banks aggressively take charge offs in order to move non-performing assets off their balance sheet, other banks have large non-performing loan pools but are not writing them off as quickly. Thus, combining these numbers gives a fuller picture of a bank's balance sheet quality.

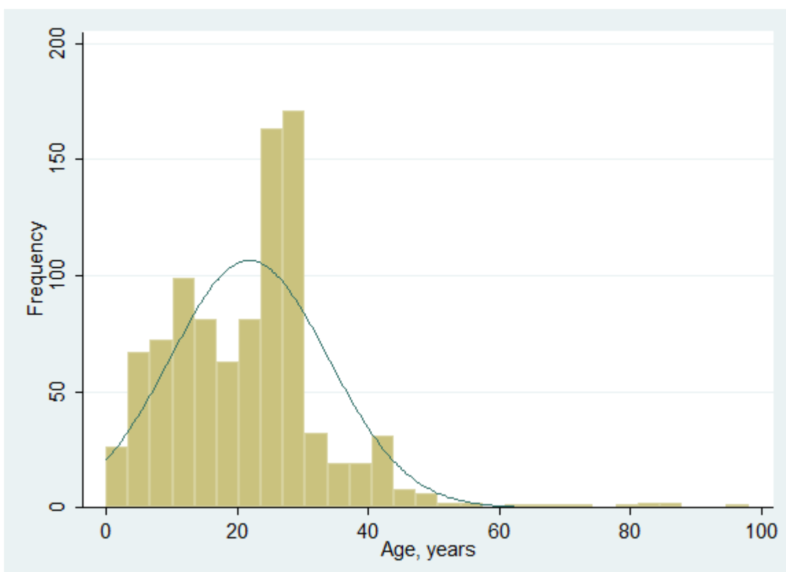
3 Testing for learning by doing

3.1 Data

This research focuses on the US because of the relatively high quality and public availability of US bank data.[18] For US bank data, I use the comprehensive and detailed data publicly available from the Federal Reserve Bank of Chicago: the FR Y-9C database comprising all domestic bank holding companies, reported on a consolidated basis. Summary statistics for the 2010 cross-section are listed in Table 5 in the Appendix.

The 2010 sample comprises 952 corporations and top-tier holding companies[19] with total assets ranging from USD85, 121 to USD2, 268, 347, 377, and age from a few months to almost 100 years old. For the age distribution, 90 percent had their charter for 33 years or less and the average bank age was just under 22 years. Of the sample of 952 banks, 156 were 10 years or younger, 237 were between 10 and 20 years old, and a bulk of 410 were between 20 and 30 years old. As can be seen in Figure 1 on page 10, the distribution includes several observations in the far right tail.

Figure 1: Distribution of Age variable for 2010 cross-section



Looking more closely at the characteristics of the banks in my dataset, Table 2 on page 11 lists average size by output (earning assets), and compares loans to total earning assets for banks subgrouped by age deciles. The largest bank by earning assets is in the oldest decile, however the first and third age deciles have the next highest maxima for Earning Assets. In all subgroups, the loan to earning assets ratio maximum does

[18] Further research using a multi-country dataset or additional case studies of countries with different banking systems and histories, would help to generalize the results of this paper.

[19] The sample excludes limited partnerships and other limited liability structures, trusts and mutuals.

not go below 90percent. However the subgroup minimum varies from 9percent for the oldest decile, to 44percent in the 5th decile. This suggests heterogeneity in the banks' asset composition is not associated with age.

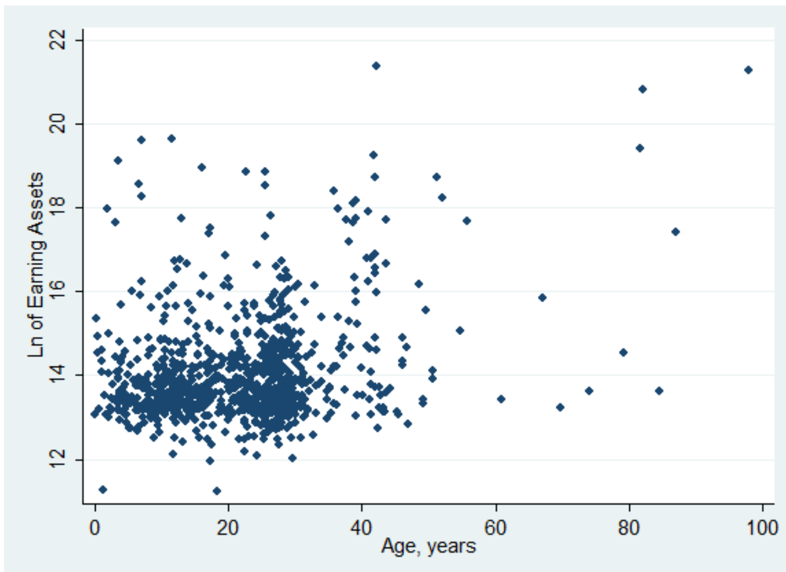
Table 2: Asset Allocation, Full Sample vs Age Deciles
Minimum, Maximum and Median values for each age decile and the full sample

Decile	Age	Earning Assets	Total Loans	Other Earning Assets	Loans/ Earning Assets
1 Min	0	77,461	56,363	21,098	0.16
Max	7	324,090,148	141,917,020	182,173,120	0.95
Median	4	760,130	567,116	217,188	0.73
2	7	273,250	233,922	23,480	0.40
	11	11,232,587	6,100,855	6,089,345	0.96
	9	742,316	550,995	206,443	0.76
3	11	181,575	117,208	17,530	0.14
	14	342,702,000	47,795,000	294,907,008	0.96
	13	834,751	624,860	258,611	0.74
4	14	75,718	47,807	27,911	0.31
	19	172,905,059	126,550,123	46,354,936	0.94
	16	819,092	615,936	210,152	0.75
5	19	195,620	142,769	27,466	0.44
	23	153,111,842	66,642,348	86,469,496	0.90
	21	950,244	616,791	265,455	0.73
6	23	174,416	143,714	27,748	0.41
	26	154,603,840	119,475,313	35,128,528	0.91
	25	823,431	578,902	239,628	0.71
7	26	257,984	132,843	34,621	0.09
	27	54,528,256	27,542,879	26,985,376	0.93
	27	813,510	621,628	248,122	0.72
8	27	231,155	141,160	16,778	0.26
	29	18,502,899	13,576,961	4,925,938	0.96
	28	922,968	643,701	293,613	0.69
9	29	163,256	111,411	19,278	0.25
	34	12,385,437	8,922,221	5,432,985	0.96
	30	965,239	660,620	266,297	0.72
10	34	335,645	183,627	46,573	0.09
	98	1,943,209,050	993,149,151	1,185,099,008	0.90
	42	2,287,370	1,690,346	700,280	0.69
Full Sample	0	75,718	47,807	16,778	0.09
	98	1,943,209,050	993,149,151	1,185,099,008	0.96
	23	875,378	622,459	258,179	0.72

For the full sample, the median loans to earning assets ratio is 72pct of earning assets, similar to the simple bank production framework emphasized above where bank output is credit. For some banks, other assets such as trading assets and short-term, liquid securities account for a higher proportion of total earning assets. The type of output mix may introduce different learning and cost dynamics.[20]

For the size distribution, the 90th percentile for Earning Assets was just under USD6bn. Not all old banks were large and not all large banks very old. For the full sample, the correlation between age and size, measured as Earning Assets, was 0.24. (For Age and size scatter plot, please see Figure 2 on page 12.) Breaking that down by age quartiles, correlation between age and size was strongest for the oldest banks (over 27.9 years of age)and negligible for the others.[21]

Figure 2: Age and Size for 2010 cross-section

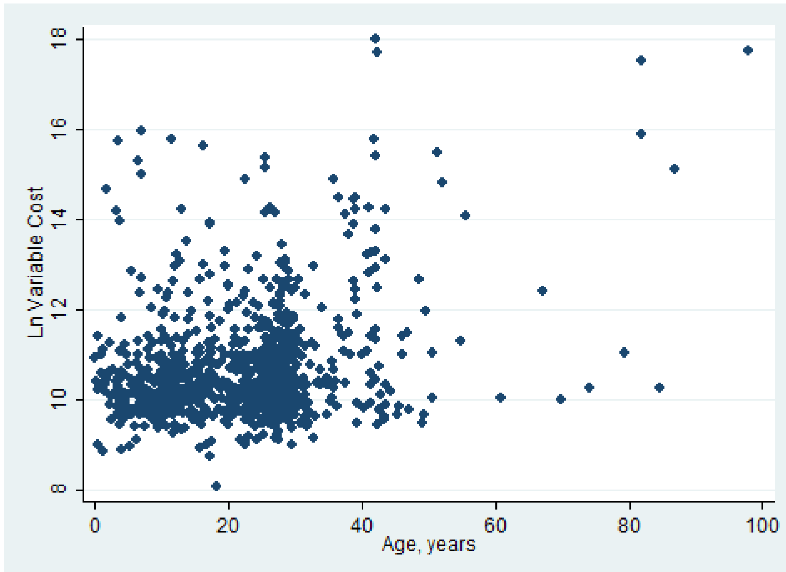


[20]As a robustness check, the 18 banks tagged as systemically important and stress tested by the Federal Reserve in March 2013 were excluded. Regression results were similar, although the coefficient estimates suggested a *greater* effect on cost from the experience variable. See Figure 7 for the plots of average marginal effects using the estimates from the reduced sample.

[21]Correlation between age and size was -0.01 for banks up to about 12.5 years of age, 0.01 for banks $12.5-23$ years old, -0.02 for $23-28$ years old, and 0.35 for banks older than 28 years.

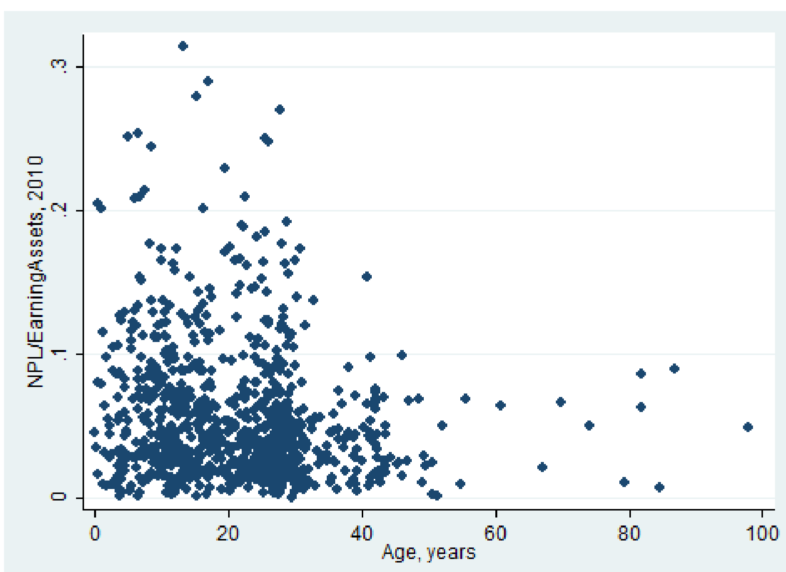
Plotting the data for the 2010 cross-section, no clear pattern emerges between variable costs and age. (See Figure 3).

Figure 3: Age and Cost for 2010 cross-section



Focusing in on *screening* efficiency, the proportion of non-performing assets to total earning assets seems to be lower for more experienced banks (See Figure 4). This provides support for a hypothesis that learning leads to better screening, fewer defaults by borrowers, and thus lower non-performing loan ratios for experienced banks.

Figure 4: Age and Non-Performing Loans for 2010 cross-section



3.2 Estimation of benchmark uncorrected model

Turning to the econometric analysis, the benchmark uncorrected econometric model

$$lnVariableCost_i =$$

$$\alpha+\beta_q lnEarningAssets_i+\sum_{j=1}^{5}\gamma_j lnW_{j,i}+\beta_k lnEquity_i+\beta_{rsk} lnRisk_i+\beta_{exp} lnAge_i+\epsilon_i \quad (5)$$

was estimated using the 2010 cross-section of banks.[22]

For the full sample, in the log-log form, the results do not suggest any cost efficiency gains from experience. The estimated coefficient on experience (Age) is significant and positive, 0.030. Based on results from DeYoung and Hasan (1998) suggesting younger banks have significantly more to gain from experience, the model is estimated using two sub-samples, the first for banks under 9 years of age, and the second for established banks over 9 years of age. Nine years was the length of time DeYoung and Hasan (1998) found it took younger banks to match established banks' profitability. Estimation results are reported in Table 3, columns 2 and 3. The coefficient estimate was negative and significant for the young bank subsample, -0.112, suggesting newer banks may be learning by doing.[23]

Based on the two sub-sample results, I revised the model, adding powers of $lnAge$ to the estimation equation.[24] Including $(lnAge)^2$ and $(lnAge)^3$, the full sample now yields the results in column (5) of Table 3.

Investigating scale and experience, interaction terms between age group and size were not significant. However using the continuous Age variable and adding an interaction term between size (Earning Assets) and experience (Age) suggests the slope does differ with firm scale. Column (6) of Table 3 on page 15, reports the coefficient estimates when scale and experience are allowed to interact. The interaction term is significant. [25] Figure 5 plots average marginal effects at representative values of $lnAge$.

The Adjusted R-squared statistic for the full sample and sub-sample models were above 90 percent, and F-tests rejected the hypothesis that the covariates had no effect on the dependent

[22] I chose 2010 because during 2009, reporting was adjusting to volatile conditions and a high degree of uncertainty.

[23] Also regressions by age deciles are reported in the endtable 6. The marginal effect of experience for the youngest decile (91 banks under 7 years of age), was -0.144 and significant at the 10pct level.

[24] It could be the case that 'forgetting' occurs (as in Benkard (2000)), or older banks balance sheet risks affect cost in a way that is not captured by the data.

[25] Calculating marginal effects using the coefficient estimates from either the specification with (Column (6)) or without (Column (5)) the interaction term suggest the beneficial effect of age on variable cost disappears after about 2 years. Without an interaction term the effect of age wanes around 2.4 years ([1.42,4.17]), with a size and age interaction in the model the effect wanes around 2 years ([1.22,3.60]).

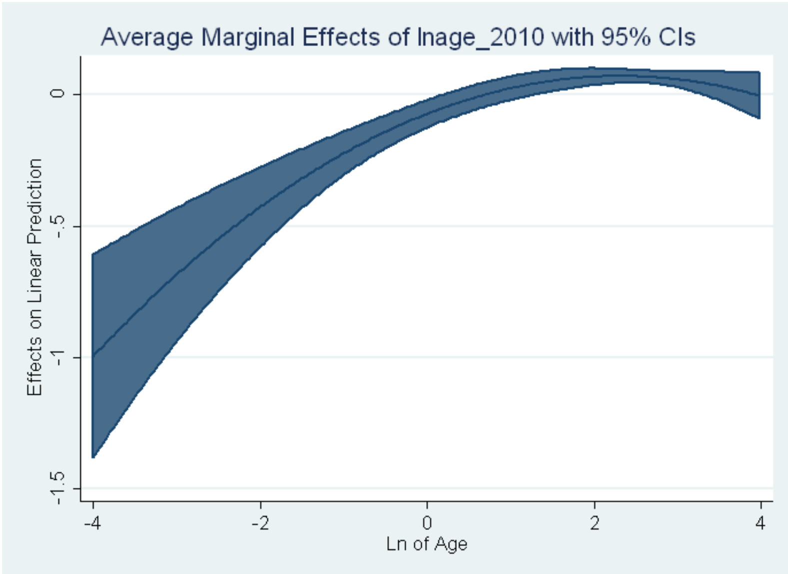
Table 3: OLS Estimation Results, Dependent variable: Variable Cost

	Full sample (1)	Age<9 (2)	Age≥9 (3)	Full sample (4)	Full sample (5)	Full sample (6)
Earning Assets	0.908***	0.924***	0.919***	0.910***	0.908***	0.841***
	(0.023)	(0.101)	(0.020)	(0.022)	(0.022)	(0.030)
Price of Labor	0.227***	0.395**	0.171***	0.254***	0.266***	0.262***
	(0.033)	(0.126)	(0.032)	(0.033)	(0.033)	(0.033)
Price of Physical Capital	0.034*	0.004	0.033**	0.035**	0.034**	0.031*
	(0.013)	(0.045)	(0.013)	(0.013)	(0.013)	(0.013)
Deposit interest rate	0.197***	0.305***	0.178***	0.215***	0.214***	0.213***
	(0.018)	(0.060)	(0.018)	(0.018)	(0.018)	(0.018)
Other Borrowed Funds interest rate	0.044***	0.089*	0.037***	0.050***	0.049***	0.048***
	(0.009)	(0.042)	(0.008)	(0.009)	(0.009)	(0.008)
Equity	0.033*	0.080	-0.001	0.027	0.032*	0.032*
	(0.016)	(0.071)	(0.015)	(0.016)	(0.016)	(0.016)
Risk	0.024*	-0.042	0.047***	0.024*	0.024*	0.022*
	(0.010)	(0.038)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.030**	-0.112*	0.072***	-0.103***	-0.088***	-0.384***
	(0.010)	(0.051)	(0.017)	(0.026)	(0.026)	(0.093)
Age^2				0.032***	0.062***	0.062***
				(0.006)	(0.011)	(0.011)
Age^3					-0.008**	-0.009***
					(0.002)	(0.002)
Interaction Age with Earning Assets						0.022***
						(0.007)
Constant	-2.667***	-2.660***	-2.677***	-2.535***	-2.708***	-1.770***
	(0.165)	(0.675)	(0.152)	(0.164)	(0.171)	(0.331)
Observations	905	133	772	905	905	905
Adjusted R^2	0.967	0.916	0.977	0.968	0.969	0.969

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

variable. The estimated coefficient on output (Earning Assets) remained significant, positive and of a similar magnitude for all the various models, and input price coefficient estimates satisfied theoretical regularity.[26]

Figure 5: Marginal effects using OLS estimates, column (6)



3.3 Estimation correcting for endogeneity and selection biases

The initial analysis suggests experience is linked to lower production costs. However the role of endogeneity and survivorship biases in the estimates need to be addressed. Simultaneity issues arise in production and cost function estimation because of correlation between the bank's choice variables (output in this case) and unobserved efficiency shocks anticipated by managers. Managers simultaneously observe input prices and choose output and could respond to lower input prices by raising output, with an ambiguous effect on variable cost. (Appendix Table 7 reports regression results estimating the effect of input prices on output (Earning Assets). The estimated coefficients on all input prices except physical capital are significant.) However assuming it is in fact these unobserved efficiency shocks that drive output decisions provides a rationale for controlling for the endogenous component of output.

With regards to bias introduced by sample dependence, during 2008-2010, 182 US banks failed according to FDIC data.[27] We therefore cannot observe the relation between cost and experience for those that exited. If we conjecture that bank failure is

[26] Input price coefficients γ_j, were not restricted to sum to 1. An F-test comparing constrained to unconstrained supported the unconstrained specification. The Risk metric was statistically insignificant in the young subsample but was significant for older banks.

[27] See the FDIC Failed Bank list. http://www.fdic.gov/bank/individual/failed/banklist.html.

a function of cost, my sample would be truncated by the dependent variable at some high-cost threshold above which the bank has gone bankrupt. As such higher cost younger banks are excluded from the analysis, and a "flatter", weaker estimated effect would result. Also, it is possible that the surviving banks are more cost efficient for some other reason than experience and thus the estimates are biased. For example, because older and larger firms may be less likely to exit at a given cost threshold than smaller and younger firms, the age coefficient could be underestimated.[28]

To formally address these biases a two-step correction method is applied. In the first stage, the probability of selection—the bank continuing to operate and thus observed in the sample—is estimated for each bank, and in the second stage these probabilities are used as instruments in the estimation of the cost function itself. The logic in brief is that by assuming an unobserved (to the econometrician) efficiency factor influences both selection and output choice, the estimate of the probability of the bank continuing provides an instrument for the unobserved efficiency factor. Therefore its inclusion in the cost equation controls for both selection and endogeneity biases.[29]

To concretize this approach rewrite the cost function with the error term ϵ_{it} as a combination of two terms. Assume the first represents an anticipated cost efficiency innovation known to the banks but unknown to the econometrician ω_{it}. The second term one can think of as an unanticipated efficiency shock, ν_{it}, the true error. With a change in notation—using lower case to represent logged variables, and adding a time subscript—we have the following expression:

$$vc_{it} = \alpha + \beta_q q_{it} + \sum_j \gamma_j w_{j,it} + \beta_k k_{it} + \beta_{rsk} rsk_{it} + \beta_{exp} exp_{it} + \omega_{it} + \nu_{it} \tag{6}$$

Since we assume the probability of bank selection is influenced by ω_{it}, which banks observe, we can write an selection equation where $D = 1$ if the bank continues, and $D = 0$ if the bank exits (via merger or liquidation)[30]:

$$D(\omega_{it}, \mathbf{H}_{it}) = 1 \text{ if } V(\omega_{it}, \mathbf{H}_{it}) < \theta \tag{7}$$

Surviving till period t thus depends on observed cost efficiency ω_{it}, along with a vector of other factors H.[31] And conditional on not exiting, greater efficiency, ω_{it} (rather than lower vc_{it}) would cause higher output. Thus including ω_{it} in the cost function controls

[28]In the Appendix, Figure 8 plots age and size and Figure 9 plots age and variable cost, comparing surviving banks to those that exited.

[29]This approach draws heavily on Heckman (1979) and Olley and Pakes (1996).

[30]I do not explicitly look at the role of regulators in this process. It is enough to assume that bank efficiency influences the continuation versus exiting outcome.

[31]For example, in many industries, including finance, larger firms (greater Q) are less likely to fail for a given realized efficiency level, than smaller firms.

for endogeneity bias.

To implement the above estimation approach, the probability of selection P is estimated for each bank using a Probit model. In the second stage these probabilities are used in the estimation of the cost function itself. For identification, at least one factor influencing continuation (in H and included in the Probit selection model), should be excluded from the cost equation. For this exclusion restriction I use regional bankruptcies and the average regional unemployment rate.[32] It is unlikely that higher firm failure rates would have a direct impact on a bank's variable cost, however this would increase the likelihood of bank failure because of the direct negative effect of increased bankruptcies on loan repayment and asset values. High unemployment rates could inhibit credit creation, worsen default rates, and signal future bankruptcies. For the selection equation, I would expect to see a negative coefficient estimate for unemployment and bankruptcies. The estimated selection equation (See Appendix Table 8 on page 26 for the Probit model estimation results.) does show both unemployment and bankruptcies are statistically significant.[33] However the sign of the coefficient on regional unemployment is positive. It could be the case that high and persistent unemployment may reduce future bank labor costs via the dampening effect on wage expectations. The Probit model was estimated using $t-1 = 2007$ to ensure a large enough number of exited banks. Consequently, the probability of selection into the 2010 sample was predicted using 2007 data. This lag may have resulted in the wage expectation channel dominating the demand shock channel. Nevertheless, for the purposes of the correction method, the key outcome of the first step is a viable estimated function of ω_{it}. Obtaining the inverse Mills ratio $\frac{f(\omega_{it},\mathbf{H}_{it})}{F(\omega_{it},\mathbf{H}_{it})}$, using the Probit selection model step provides this function. This then becomes the instrument for ω_{it} in the corrected model.

Table 4 reports estimation results for the initial model and the corrected model. In Column 2, the first corrected model specification shows the estimates when only the inverse Mills ratio (P) is included. Following the logic of Olley and Pakes (1996), the second specification also includes P^2 and P^3. The estimated average marginal effect[34] of age does differ from the initial results. Using the uncorrected model, the overall average marginal effect was 0.047 with a 95pct confidence interval of $[0.017, 0.077]$. Using the model in column (3) of Table 4, the overall average marginal effect (the average of marginal effects at representative values of $lnAge$) was 0.030 with a 95pct confidence

[32] The US data is grouped into 12 regions based on the Federal Reserve system districts. See Benkard (2000) for examples of other demand shock proxies used in production function estimation.

[33] Although for the selection equation the estimated coefficient on bankruptcies was 0.000, using regional unemployment alone resulted in the variable being statistically insignificant.

[34] Because all of the variables used are in log form, marginal effects are proportional, and one can think of them as elasticities. I will refer to marginal effects throughout the paper.

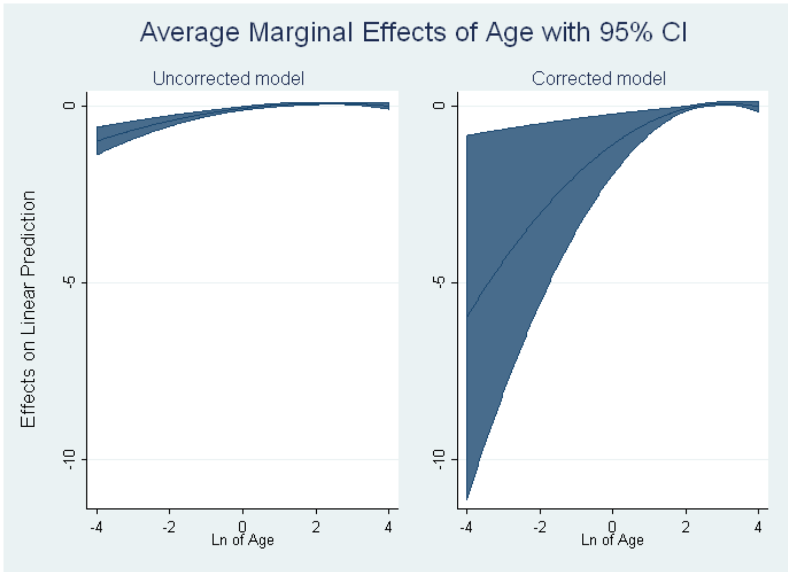
Table 4: OLS vs Corrected Estimation Results
Dependent Variable: Variable Cost

	OLS (1)	**P only** (2)	**Powers of P** (3)
Earning Assets	0.841***	0.891***	0.880***
	(0.030)	(0.038)	(0.039)
Price of Labor	0.262***	0.327***	0.323***
	(0.033)	(0.044)	(0.045)
Price of Physical Capital	0.031***	0.030*	0.033**
	(0.013)	(0.015)	(0.015)
Deposit interest rate	0.213***	0.198***	0.201***
	(0.018)	(0.022)	(0.022)
Other Borrowed Funds interest rate	0.048***	0.032***	0.032***
	(0.009)	(0.009)	(0.009)
Equity	0.033**	0.002	0.006
	(0.016)	(0.020)	(0.021)
Risk	0.022**	0.040***	0.041***
	(0.009)	(0.011)	(0.011)
Age	-0.384***	-1.130**	-1.207**
	(0.093)	(0.492)	(0.497)
Age^2	0.061***	0.354**	0.372**
	(0.012)	(0.159)	(0.160)
Age^3	-0.009***	-0.038**	-0.040**
	(0.002)	(0.019)	(0.019)
Interaction	0.022***	0.007	0.008
Age with Earning Assets	(0.007)	(0.009)	(0.009)
Constant	-1.770***	-1.573**	-1.406**
	(0.331)	(0.656)	(0.675)
N	905	726	726
R^2	0.97	0.97	0.97
$F_{(11,893)}$	2560		
$F_{(12,713)}$		2247	
$F_{(14,711)}$			1925

Significance levels: $*$: 10% $**$: 5% $***$: 1%. Standard errors in parentheses.

interval of $[-0.006, 0.066]$. Plotting marginal effects at different representative values of $lnAge$ illustrates how the overall average marginal effect hides the beneficial effects of age on cost for younger banks. (See Figure 6.)

Figure 6: Marginal effects comparison: uncorrected (1) vs. corrected model (3)



The corrected model implies the marginal effect of age on cost remains beneficial until around 10 years of age, rather than the 2 years implied by the benchmark OLS estimation. (See Figure 6 comparing the plots of the corrected and uncorrected estimation models.) More specifically, after correcting for biases, the estimated marginal effect of age on variable cost is decreasing and turns to zero at 10.6 years of age.[35] The upper bound of the 95th percentile confidence interval around the estimated effect of age, turns positive at 7.8 years of age. And the lower bound of the confidence interval turns positive around 15 years of age. In comparison, for the uncorrected model, the range is 1.2 to 3.6 years.

4 Conclusion and implications

In conclusion, empirical evidence suggests experience is associated with cost efficiency gains in banking. Using a learning by doing cost function model, the estimated average marginal effects of experience remained beneficial for banks up to around 1.2 to 2 years of age. However, correcting for selection and endogeneity biases, experience effects remain beneficial for banks up to around 10.5 years of age. The results from the corrected estimation model yielded larger coefficients on age, although with larger

[35]The derivative of $lnVariabeCost$ with respect to $lnAge$ becomes 0 at $lnAge = 2.36$ in Figure 6.

standard errors associated with these estimates. Nevertheless the coefficients remained statistically significant at the 5 percent level. Computing average marginal effects, the gains from experience are most intense for the youngest banks. For example, on average, a 10 percent increase in experience for a bank of around 1 year of age is associated with a 10.9 percent decline in variable cost; for a 5 year old bank, an additional 6 months of experience is associated with a 2 percent cost decline. The results from this paper complements the evidence in DeYoung and Hasan (1998) that start up banks in the 1990s on average took nine years to become as profitable as an established bank, with more than half of the gains made during the first three years of operation.

If experience does have a role to play in developing the capabilities of financial intermediaries, policymakers have an additional motivation to facilitate financial activity, whether via liberalizing domestic financial markets or opening up to global trade and global capital flows. In addition to the direct effects of these policies, increased financial activity could bring the indirect effect of improving financial sector efficiency. Any argument for increasing financial activity seems suspect in the aftermath of a finance boom and bust such as the one experienced by the developed world in 2008-09. Prior to this crisis, research on growth and finance had shown that domestic financial development, typically measured as private sector credit to GDP, has a positive effect on economic growth. King and Levine (1993), Levine et al. (2000) used panel data to show well-developed financial systems can boost growth, and Levine and Zervos (1998) demonstrated both banking and stockmarket capabilities positively affected growth. Updating this line of research, Deidda and Fattouh (2002), Rioja and Valev (2004) found a positive but non-linear relationship between financial development and growth.Cecchetti and Kharroubi (2012) using a sample of developed and developing economies, showed that financial development promotes aggregate productivity growth but only up to a certain point. The authors argue that there comes a point when the financial sector draws resources away from other industries and becomes a drag on overall productivity growth. For those economies below this threshold, financial development is desirable, and with experience a factor, greater financial activity could facilitate financial development.

Active participation in global markets may also bring indirect benefits if accumulated experience in these markets leads to greater financial efficiency. Of course, capital inflows can surge and also stop suddenly, putting pressure on the exchange rate and destabilizing the recipient economy's financial sector. The crises of the 1990s and early 2000s illustrated these risks of the "Washington consensus" that countries should fully open their capital accounts. However, more recent research on capital-account liberalization, including Kose et al. (2011), has argued that a country that first achieves a threshold level of financial and institutional development, will more likely accrue the benefits of opening the capital account with less vulnerability to crises. Consequently the development of the domestic financial system is important both as preparation for greater capital-account openness; and subsequently as the capital account is opened, experience with international financial activity could further improve financial sector efficiency.

Further research is needed to generalize these results and to analyze the degree of knowledge spillovers in the banking sector. Historical data in the US that coincided with branching regulatory changes or industry innovation could be used to explore whether knowledge spread between banks in different states, or metropolitan areas, or between branches within a state. Additional single country case studies of countries with banking systems dissimilar to the US, such as Canada, could clarify whether industry structure or some omitted attribute is driving the US result. Internationally, using a multi-country dataset would gauge whether firm-specific experience effects are evident in other countries, and whether spillovers occur at the country and global level.

Table 5: Summary Statistics

Variable (USD, 000s)	Mean	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Variable cost	385,282	3,135	20,589	30,887	60,624	64,223,637
Earning assets (output)	12,479,761	75,718	582,045	875,378	1,798,673	1,943,209,050
W_1 (labor)	69.17	19.39	55.37	63.29	75.62	383.53
W_2 (physical capital)	0.320	0.038	0.159	0.217	0.325	3.965
W_3 (deposits)	0.012	0.000	0.008	0.012	0.015	0.036
W_5 (other borrowed funds)	0.114	0.000	0.022	0.036	0.049	50.136
Equity	1,825,257	-23,736	60,678	95,238	209,337	317,195,588
Risk	693,039	0	17,940	38,052	99,288	127,511,443
Age, years	21.85	0.04	12.54	22.96	27.91	98.00
Total assets	14,035,930	85,121	629,057	944,064	1,945,596	2,268,347,377

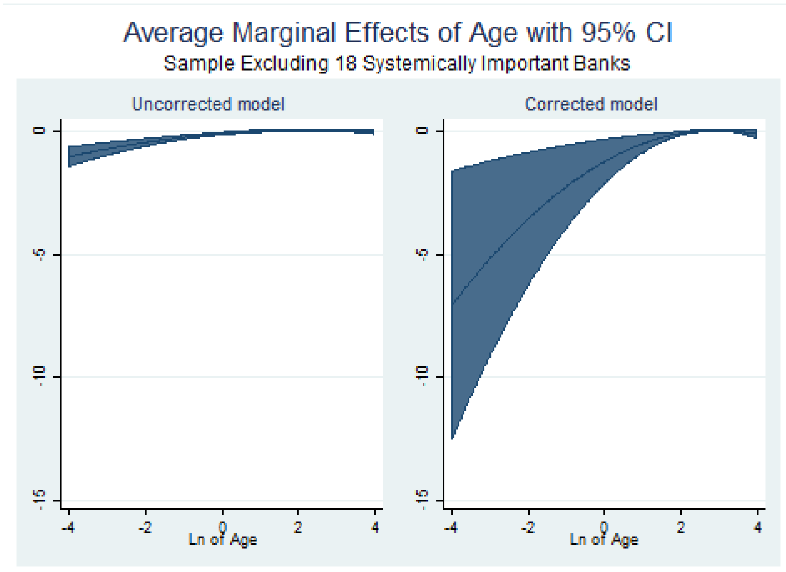
Table 6: Regression by Age deciles, Dependent variable: Variable Cost

	1	2	3	4	5	6	7	8	9	10
Earning Assets	0.941***	0.932***	0.938***	0.950***	0.827***	0.942***	0.660***	0.957***	0.970***	0.924***
	(0.14)	(0.06)	(0.03)	(0.05)	(0.06)	(0.09)	(0.09)	(0.07)	(0.08)	(0.08)
Price of Labor	0.384*	0.011	-0.017	0.123	0.196*	-0.008	0.437***	0.224*	0.012	0.345***
	(0.17)	(0.07)	(0.07)	(0.09)	(0.10)	(0.13)	(0.11)	(0.09)	(0.11)	(0.09)
Price of Physical Capital	0.040	-0.022	0.033	0.052	0.123**	0.051	-0.047	0.114***	0.033	0.043
	(0.07)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)
Deposit interest rate	0.314***	0.139**	0.044	0.347***	0.301***	-0.014	0.244***	0.362***	0.068	0.172***
	(0.07)	(0.05)	(0.04)	(0.06)	(0.07)	(0.07)	(0.07)	(0.04)	(0.06)	(0.04)
Other Borrowed Funds interest rate	0.100	0.013	0.022	0.013	-0.011	0.043	0.099**	0.058**	0.025	0.075**
	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Equity	0.090	-0.010	-0.066**	-0.041	0.085	-0.070	0.253***	0.030	-0.054	0.024
	(0.10)	(0.04)	(0.02)	(0.03)	(0.04)	(0.08)	(0.07)	(0.05)	(0.06)	(0.08)
Risk	-0.053	0.023	0.069**	0.056*	0.033	0.072*	0.033	-0.011	0.042	0.027
	(0.05)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Age	-0.144*	0.161	0.047	0.236	0.101	0.877	0.475	1.158	-0.576	0.152
	(0.07)	(0.13)	(0.22)	(0.33)	(0.31)	(0.80)	(1.53)	(1.04)	(0.42)	(0.09)
Constant	-2.688**	-2.352***	-2.225**	-2.290*	-1.908	-5.120	-3.942	-5.752	-0.406	-3.797***
	(0.89)	(0.51)	(0.67)	(1.11)	(1.08)	(2.59)	(5.12)	(3.41)	(1.56)	(0.52)
N	91	92	92	91	89	90	89	89	89	93
R^2	0.92	0.96	0.98	0.97	0.97	0.96	0.95	0.98	0.97	0.99

Significance levels: $*$: 10% $**$: 5% $***$: 1%. Standard errors in parentheses.

A Age and size

Figure 7: Marginal effects excluding very large banks



B Endogeneity and selection

Table 7: Effect of input prices on output choice
Dependent Variable: Earning Assets

Variable	Coefficient	(Std. Err.)
Price of Labor	1.028***	(0.158)
Price of Physical Capital	0.116	(0.066)
Deposit interest rate	-0.788***	(0.081)
Other Borrowed Funds interest rate	-0.163***	(0.042)
Constant	5.820***	(0.747)
Observations		909
Adjusted R^2		0.215

Significance levels : $*$: 10% $**$: 5% $* * *$: 1%

Table 8: Probit selection model
Used in two-step correction, Dependent Variable: Selection

Variable	Coefficient	(Std. Err.)
Earning Assets	-0.046	(0.178)
Price of Labor	-1.055***	(0.244)
Price of Physical Capital	-0.128	(0.096)
Deposit interest rate	-0.708***	(0.243)
Other Borrowed Funds interest rate	-0.086	(0.075)
Equity	0.325**	(0.155)
Risk	-0.201***	(0.061)
Age	0.095	(0.070)
Regional Bankruptcies	0.000***	(0.000)
Regional Unemployment	0.264**	(0.117)
Constant	0.285	(1.376)

Significance levels : $*$: 10% $**$: 5% $* * *$: 1%

Figure 8: Age, Size for selected vs unselected

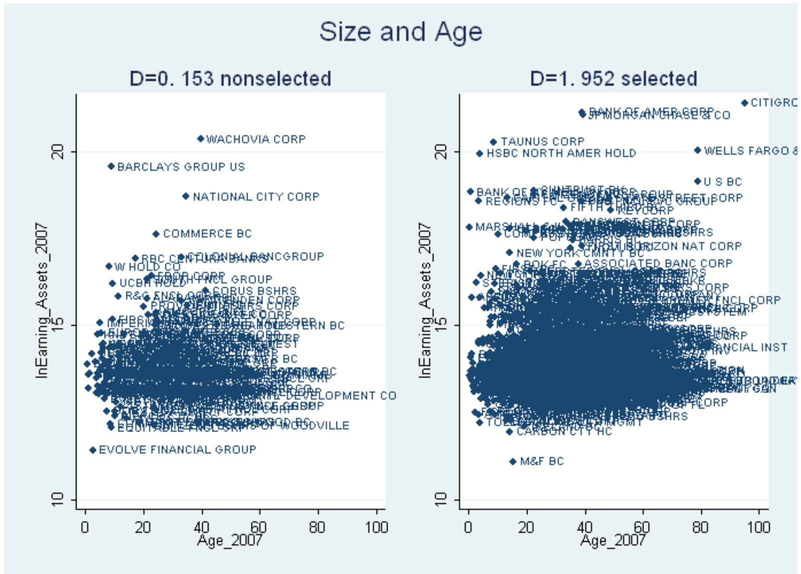
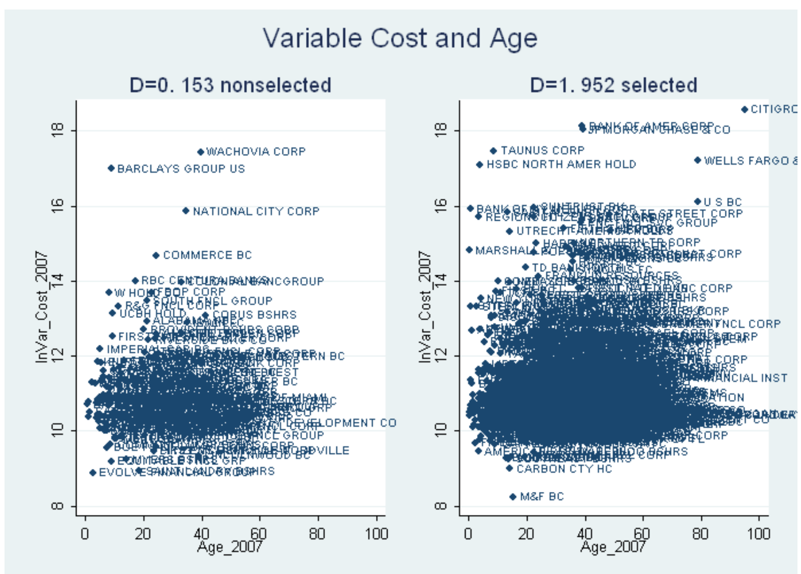


Figure 9: Age, Variable Cost for selected vs unselected



C Functional form: Translog specification

Much of the research on learning by doing uses industrial or manufacturing production specifications with Cobb-Douglas functional forms, as I have used in the body of this paper. However, more flexible functional forms have been used to analyze banking production and as a robustness check the translog functional form is used in the analysis that follows. Consider a second-order translog approximation of the variable cost function:

$$lnVC = \alpha_0 + \sum_i \alpha_i lnZ_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} lnZ_i lnZ_j \tag{8}$$

where Z is the vector of cost inputs, in my model $Z = (Q, W_p, W_d, K, RSK, EXP)$. Invoking Shephard's lemma and duality theory, demand for input j is equivalent to the partial derivative of the cost function with respect to the price of that variable input. Factor "share" equations are derived where input j accounts for share S_j of costs, and of course the shares add to one, $\sum_j S_j = 1$.[36]

$$\frac{\partial lnVC}{\partial lnw_j} = S_j = \alpha_j + \sum_i \beta_{ij} lnZ_i \tag{9}$$

Estimating the model requires a systems approach because of the multiple equations: the variable cost function, and four share equations— for W_1 (labor), W_2 (physical capital), W_3 (deposits), W_5 (other borrowed funds). One can plausibly assume error terms are not correlated across banks, however correlation between the system equation errors is nonzero. Thus the estimator needs to allow for this. I used a Seemingly Unrelated Regression estimator. The parameters in the share equations are subsets of those in the cost equation. Thus estimating the system of equations can generate more efficient estimates, with some restrictions. The "adding up" constraint on the share equations can be used, and one share equation dropped.[37] I dropped the physical capital share equation. And, symmetry restrictions were imposed on the cross-partial derivatives, $\beta_{ij} = \beta_{ji}$. In Table 9, two different specifications are reported, one with only symmetry restrictions, the other with the restriction that $\sum_i \beta_{ij} = 0$. In both, the coefficient on age is the correct sign (negative) and statistically significant.

Average marginal effects (AMEs) at representative values are calculated using the Translog model with symmetry imposed, and plotted in Figure 10. The effect is negative, decreasing and evident up to banks of around 5 years of age. (The derivative turns to 0 at 4.57 years.) The upper bound of a 95pct confidence interval around the AME turns to 0 at 2 years, the lower bound at just under 7 years. (Note that the Translog estimation does not specifically address the biases involved in estimating cost functions. Full Translog estimation results used to calculate AMEs and available on request; interaction term coefficients not reported in the table.)

[36] For example, Bossone and Lee (2004), Hughes and Mester (1998), Hunter and Timme (1986) used a similar approach.

[37] Since the share equations add to one, they are not linearly independent.

Figure 10: Marginal effects using Translog estimates

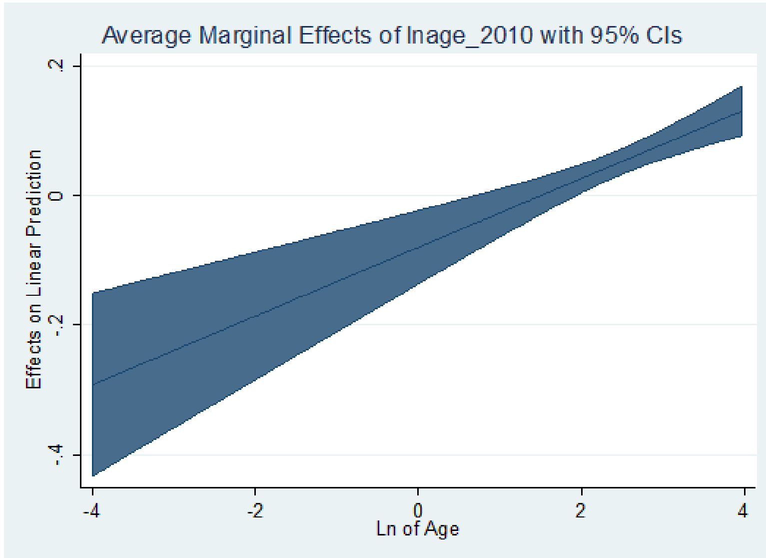


Table 9: Translog Functional Form

Dependent Variable: Variable Cost

	Symmetry only (1)	Symmetry and betas sum to 0 (2)
Earning Assets	1.867***	1.865***
	(0.23)	(0.23)
Price of Labor	-1.939***	-2.071***
	(0.45)	(0.42)
Price of Physical Capital	0.115	0.106
	(0.20)	(0.20)
Deposit interest rate	1.588***	1.546***
	(0.24)	(0.23)
Other Borrowed Funds interest rate	-0.025	-0.042
	(0.13)	(0.13)
Equity	-0.960***	-0.965***
	(0.20)	(0.20)
Risk	0.101	0.105
	(0.13)	(0.13)
Age	-0.430**	-0.462***
	(0.13)	(0.13)
Constant	4.825***	5.039***
	(1.21)	(1.18)

Significance levels: $*$: 10% $**$: 5% $***$: 1%. Standard errors in parentheses.

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