Comparisons of Deposit Types and Implications of the Financial Crisis: Evidence for U.S. Banks

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March 2020

Abstract

This paper makes three diverse contributions. First, whereas the extant literature estimates a single elasticity of substitution/complementarity from an input distance function, we calculate a range of elasticities. Second, we make a substantive contribution to the literature on bank input substitution/complementarity because somewhat surprisingly there has been very little work on this issue. Third, our analysis of the substitutability/complementarity of deposit types for U.S. banks in 2008 – 2015 (crisis and beyond), vis-à-vis 1992 – 2007 (pre-crisis), is, to the best of our knowledge, the first to consider the effect of structural change on elasticities of substitution/complementarity. To account for the extent of the heterogeneity in the U.S. banking industry we estimate random coefficients models, as opposed to standard fixed parameter models. The key empirical findings are the changes in the substitutability/complementarity of the quantities of particular pairs of deposit types between the two sample periods, which points to changes in depositors' preferences across banks' deposit portfolios. To illustrate, for savings deposits, which are characterized by flexibility and liquidity, and time deposits, which are less so and thus have higher interest rates, we find significantly lower quantity complementarity in 2008 – 2015. From this finding we can conclude that savings and time deposits have become more distinct, which we suggest should be reflected in banks' strategic management of their deposit portfolios.

Key words: Input substitution/complementarity; Deposit types; Financial crisis; U.S. banks; Bank strategy and decision-making.

JEL Classification: C23; D24; G21.

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1 Introduction

The financial crisis was a watershed as it marked the beginning of a period of great change that involved various policies and reforms to moderate the resulting Great Recession and reduce the risk of a similar crisis in the future. Among other things, during this period there were marked changes in depositors' preferences across U.S. banks' deposit portfolios. This is evident from figure 1, which presents for the U.S. banking system for $1992-2015$ three disaggregations of real total deposits into different deposit categories.[1] To illustrate, panel B of this figure reveals that savings deposits increased sharply since the crisis circa 2008, while time deposits have declined steadily. Here we analyze this and other crisis induced changes in depositors' preferences, and such an analysis can be used to inform the deposit management of U.S. banks. In the next section we motivate our analysis by discussing the crisis induced U.S. banking system developments in the context of the roles they may have played in the changing relationships between deposit categories. Since in the intermediation approach to banking (Sealey and Lindley, 1977) deposits are viewed as inputs in the production process of the banking firm, we approach our analysis from the perspective of changes in input elasticities of substitution and complementarity for pairs of deposit types.

[Insert figure 1 about here]

Rather than calculate elasticities of substitution and complementarity from a cost function, which is common in the literature (e.g., Berndt and Wood, 1975, Athanasios *et al.*, 1990, and Michaelides *et al.*, 2015), we calculate these elasticities from an input distance function (IDF). In contrast to the multiple input and single output production function, the IDF technology is in terms of multiple inputs being used to produce multiple outputs. To analyze changes in deposit type substitution/complementarity, we must estimate an IDF because although our data set for U.S. banks is extremely rich, input price data is not available for all the deposit types in figure 1 for a cost function analysis. Directly from a fitted IDF therefore we obtain primal elasticities of complementarity, which measure the degree of substitutability/complementarity between the quantities of a pair of inputs. Having estimated an IDF and without the need to estimate its dual cost function, by drawing on this duality and following some simple rearranging we obtain dual elasticities of substitution, which measure the degree of price substitutability/complementarity between a pair of inputs. In other words, dual elasticities of substitution that we would obtain directly from a cost function are obtained indirectly from an IDF. Additionally, as the rate of interest on a deposit type is taken to be the price paid by a bank to attract deposits, by obtaining dual elasticities of substitution indirectly from an IDF we circumvent the non-standard case of non-interest bearing deposits whose price is zero, which from panel C of figure 1 we can see is a non-negligible deposit category.

Our paper makes three diverse contributions. The first involves extending the study by Stern (2010), who derives the shadow elasticity of complementarity and shows how to calculate it from a fitted IDF. In contrast, instead of estimating a single elasticity of substitution/complementarity from an IDF, to foster comparisons we demonstrate how to compute a

[1] This data is available from the Federal Deposit Insurance Corporation (FDIC) and is provided in the Reports of Condition and Income (i.e., Call Reports) that U.S. banks are required to complete.

wider range of elasticities, which are a mix of symmetric and asymmetric elasticities.[2] Our analysis also reaffirms the importance of the long-established theoretical literature on elasticities of substitution and complementarity for applications to contemporary issues in banking and other areas. We compute the following six elasticities of substitution and complementarity, which we present and discuss in detail in due course: (i) Antonelli elasticity of complementarity (AEC); (ii) Allen-Uzawa elasticity of substitution (AES); (iii) Morishima elasticity of substitution (MES); (iv) Morishima elasticity of complementarity (MEC); (v) shadow elasticity of substitution (SES); and (vi) shadow elasticity of complementarity (SEC), where the extant literature focuses on calculating only the SEC from an IDF. To calculate these six elasticities we adopt a schematic approach that is based on the AEC because from the AEC we obtain the AES, MEC and SEC, and from the AES we calculate the SES and the MES.

We calculate a wide range of elasticities of substitution and complementarity because different elasticity measures provide different information. To illustrate, an AEC or MEC (both of which are obtained directly from the IDF and are therefore primal elasticities) > 0 (< 0) indicates that two inputs are quantity, q, complements (substitutes). An AES or MES (both of which are obtained indirectly from the IDF and are therefore dual elasticities) > 0 (< 0) indicates that two inputs are price, p, substitutes (complements).[3] The SEC and the SES, on the other hand, measure the degree of difficulty of q substitution and p substitution, respectively (Stern, 2011). This raises the issue of what information we are most interested in. For our purposes we are particularly interested in the AEC and AES and to a lesser extent the MEC and MES. This is because based on a point Stern (2011) makes about the appropriateness of the Morishima measures depending on the number of inputs in the analysis, the Allen-Uzawa measures are more relevant to our empirical setting (see the application for further discussion of this).

Furthermore, assuming a systematic two-stage bank decision-making process on deposit type substitution/complementarity, we are interested in the AEC, AES, MEC and MES because they can be used in the first stage to inform which deposit types are substitutes/complements. Given this knowledge, in the second stage the SEC and SES can be used to inform how viable it is to substitute between deposit types. As we elaborate on next, this is in the context of the paucity of studies that consider elasticities of substitution/complementarity for deposit types. We therefore focus on informing the first stage of this decision-making process as this is the logical approach to develop this small body of literature. We do though report empirical estimates of the SEC and SES for completeness and to acknowledge the role they can play in the second stage of the process.

As we have touched on, our second contribution is to significantly add to the literature on bank input substitution. Despite there being a prominent related literature on bank efficiency and productivity, as well as a number of empirical applications of elasticities of substitution/complementarity in other areas, Athanasios *et al.* (1990) and Michaelides *et al.* (2015)

[2] Moreover, all the elasticities of substitution and complementarity we compute are net elasticities because they are net of an output quantity change as output is held constant. In contrast, gross elasticities measure input substitution/complementarity when the output level is permitted to change.

[3] An increase in a q substitute (complement) reduces (increases) the marginal product of the other substitutable (complementary) input. Two inputs are p substitutes (complements) if, when the price of one input rises, the quantity of the other increases (decreases).

are the only studies on bank input substitution. A legacy of the seminal application on input substitution by Berndt and Wood (1975) is that subsequent applications have been concentrated in the same area and thus focus on substitution between the energy and capital inputs in industrial production. The prevalence of this type of application prompted the meta-analysis of reported elasticities between energy and capital by Koetse *et al.* (2008).

We extend both of the above studies on bank input substitution via our third contribution as well as by: (i) using up-to-date data; (ii) computing a lot more types of elasticities; and (iii) examining multiple rich disaggregations of total deposits. In contrast, Athanasios *et al.* (1990) only calculate the AES and Michaelides *et al.* (2015) only compute the MES. Although the latter is a recent study of U.S. banks the authors use data for the period $1989-2000$. This is because their focus is on the development and demonstration of a new econometric estimator of a model rather than on issues relating to the financial crisis. Moreover, although both these studies obviously account for deposits, only the latter disaggregates interest bearing deposits into a portion of panel C in figure 1 (interest-bearing transaction and non-transaction accounts). We, on the other hand, analyze all the different disaggregations of total deposits in figure 1. The third contribution of our paper is that, to the best of our knowledge, we are the first to analyze the effect of structural change on elasticities of substitution/complementarity. This is because the major developments in the U.S. banking system in response to the crisis clearly invoked structural change in the industry. This suggests that there is plenty of scope for other applications of our approach because there are a lot of cases in banking industries where policy intervention has initiated structural change, e.g., market deregulation/liberalization.

Finally, we note for various pairs of deposit types that a key empirical finding is the change in their q substitutes/complements classification between the pre-crisis period $(1992-2007)$ and the period covering the crisis and beyond $(2008-2015)$. To illustrate, for the pre-crisis period the AEC for interest-bearing and non-interest-bearing deposits suggests that the quantities of these deposit types are independent of one another. For the period covering the crisis and beyond, however, the AEC indicates that the quantities of these two deposit types are substitutes, which points to a change in depositors' preferences between these two deposit categories. In light of such findings an interesting area for further research would be to examine the determinants of such changes in preferences between deposit types.

The remainder of this paper is organized as follows. To set the scene, in section 2 we discuss the crisis induced U.S. banking system developments in the context of the roles they may have played in the changing relationships between deposit types. Since a modeling framework needs to be followed to calculate the elasticities of substitution and complementarity, we set out the framework in section 3, which consists of two parts. In the first part we provide an overview of the duality between the IDF and the cost function, as we rely on this duality to calculate the dual elasticities of substitution. The second part discusses random coefficients modeling, as we use this approach (rather than a standard fixed parameter model) to estimate the IDF to better account for the extent of the heterogeneity between U.S. banks. In section 4 we present the general form of the six elasticities of substitution and complementarity we calculate. Section 5 focuses on the empirical analysis of differences in the substitutability/complementarity of deposit types between the pre-crisis period and the period covering the crisis and beyond.

Section 6 then concludes by putting into context some of our salient findings on deposit type substitution and complementarity by describing some general banking situations that fit with such findings.

2 U.S. Banking System Developments and the Changing Relationships between Deposit Types

We adopt a logical structure for the discussion in this section by considering the role that U.S. banking system developments may have played in the changing relationships between the levels of deposit types in figure 1 from the crisis onwards. At the outset we note that total deposits trends upwards over the period $2008 - 2015$ (see figure 2). This is because, despite the impact of the crisis induced recession, the U.S. economy grew over this period, and, as a result, the amount of U.S. currency in circulation increased (Rudebusch, 2018), which will have in part manifested itself in the form of larger deposits. To illustrate, over this period U.S. real GDP increased by 11.47% and the U.S. monetary base (M0) increased by a factor of 4.51. The interesting issue for our purposes is when we compare figures 1 and 2, we can see that there are clear similarities/differences between the changes since the crisis in the level of total deposits and the levels of some deposit types. It is these similarities and differences that we focus on for the most part in the remainder of this section.

[Insert figure 2 about here]

We can see from figure 1 that the 2008 crisis led to very similar immediate falls in non-transaction accounts, savings deposits and interest bearing deposits (panels A-C of this figure, respectively). The similarity between these immediate falls in the levels of these deposit types is of course because the categories overlap (savings deposits of course form part of non-transaction accounts and interest bearing deposits). Given the gravity of the crisis, striking features of these three deposit categories are how relatively small and short-lived were, first, their falls in 2008 and, second, any subsequent fluctuations. This was followed by the start of relatively stable upward trends in all three categories over the remainder of our study period. In the case of non-transaction accounts and interest bearing deposits these upward trends closely resembled their pre-crisis trends. In the latter portion of our study period, however, savings deposits rose much faster than before the crisis.

It follows from the range of policy responses to the crisis that there are various reasons for the above small and short-lived impacts on the levels of non-transaction accounts, saving deposits and interest bearing deposits, and their subsequent relatively stable upward trends. Notwithstanding this, we now turn to discuss how the evolution of the levels of these three categories over the period covering the crisis and beyond may have been influenced by four important crisis induced developments.

1. *Quantitative Easing (QE)*

The typical monetary policy tool of the Federal Reserve is to use open market operations to influence its short term policy rate, such that the federal funds effective rate coincides with the Fed's target for this rate, as chosen by the FOMC.[4] In doing so the Fed is able to directly manipulate the supply of base money and indirectly control the total money supply.

The Fed's typical expansionary policy tool of cutting its target for the federal funds rate was not a feasible response to the crisis induced recession because the rate was already effectively at its lower limit near zero. Additionally, given the depth of the Great Recession, leaving the low federal funds rate unchanged would not on its own have revived output and employment growth sufficiently. The Fed's response therefore was to use unconventional monetary policy (Kuttner, 2018), a key part of which was QE. QE involved three waves of substantial purchases by the Fed of longer term agency backed securities to place downward pressure on longer term interest rates to ease overall financial conditions. At the start of the crisis the Fed's holding of domestic securities was less than $1 trillion, but following the three waves the Fed's balance sheet increased to over $4 trillion. QE was instrumental in stimulating the economic recovery and along with the growth in the recovery period there was the associated increase in the monetary base. This increase in base money supply will have in part manifested itself through larger deposits, which is consistent with the relatively stable upward trends in the post-crisis period in the levels of non-transaction accounts, savings deposits and interest bearing deposits.

Savings deposits may have increased particularly fast in the first part of the recovery (2010 and 2011) because of the effect of the liquidity trap (i.e., a situation where typical monetary policy using open market operations is ineffective because interest rates are low and savings rates are high). In a liquidity trap funds are put into savings rather than bonds because interest rates are expected to rise soon, which discourages holding bonds as it will push down their prices. In 2010 and 2011 market investors anticipated that the federal funds rate would soon rise (Rudebusch, 2018), but, as we will discuss further in 3. below, this turned out not to be the case.

2. *Insufficient Initial Stimulation of Bank Lending*

A key feature of the crisis was the sudden end of the credit boom. Among other things, markets for securitized assets (except for mortgage securities with government guarantees) shut down, which tended to leave concerning levels of complex credit products and other illiquid assets of uncertain value on the balance sheets of financial institutions. As a result, the U.S. banking system was in need of a substantial injection of short term liquidity. The Fed took steps to provide this liquidity by creating reserve balances for sound financial institutions using a number of new facilities for auctioning credit. These new facilities included increasing the term of discount window loans from overnight to 90 days and creating the Term Securities Lending Facility, which auctions credit to depository institutions for up to three months.

A key motivation of the Fed for this liquidity provision was to reduce banks' funding stresses. All else equal, such provision should make banks more willing to lend, thereby aiding the economic recovery. In the initial years that followed the crisis, however, this increase in lending did not materialize. A key reason for this was the introduction of a rate of interest on bank reserves at the Fed, which at the time was somewhat above the overnight federal funds lending

[4] The federal funds effective rate is the weighted average of the overnight rates that depository institutions (banks and credit unions) negotiate with one another, when those with surplus reserve balances at the Fed lend on an uncollateralized basis to those that need larger balances.

rate. Also, in response to the crisis banks became acutely risk averse. The upshot was that banks did not use large portions of their Fed reserves to finance lending, which were instead left idle.

Since the epicenter of the crisis was the turn of the U.S. housing cycle and the associated rise in delinquencies on subprime mortgages, which imposed substantial losses on many financial institutions and shook investor confidence, other things being equal, there will have been more post-crisis risk aversion from both lenders and borrowers towards mortgages vis-à-vis other loans. This is evident from figure 3 because we can see that real estate lending in the U.S. flatlined since the 2008 crisis, while there is clear evidence in 2012 of an upturn in aggregate net loans and leases.[5] As a consequence, it is conceivable in the uncertain times during the crisis and beyond that borrowers chose to keep the funds they planned to add to their borrowings for spending and investment purposes liquid in deposit accounts. Such behavior is consistent with the upward trends in non-transaction accounts, savings deposits and interest bearing deposits that we observed above following the crisis (see figure 1).

[Insert figure 3 about here]

3. *Low Federal Funds Rate Forward Guidance*

While early in the recovery market investors anticipated that the federal funds rate would soon rise, the severity of the recession and the conventional monetary policy shortfall (i.e., the shortfall between what the Fed could deliver with open market operations and what was appropriate in such a deep recession) resulted in the Fed having a different view. The Fed was instead of the opinion that a low federal funds rate was needed for an extended period, which was conditional on the expected economic conditions going forward being realized. As Rudebusch (2018) notes, on January 25, 2012, the FOMC conveyed this to investors when it stated that 'economic conditions...are likely to warrant exceptionally low levels for the federal funds rate at least through late 2014'. Given the depth of the recession and the conventional monetary policy shortfall, in this forward guidance communication the FOMC provided more certainty about the federal funds rate going forward than it would ordinarily do in such statements. The FOMC provided this greater certainty to drive down longer term interest rates by pushing down expectations of the federal funds rate going forward, and thereby promoting growth.

Growth is accompanied by an increase in the monetary base, which will have in part manifested itself through the larger deposits we observed in the post-crisis period (i.e., the relatively stable upward trends over this period in non-transaction accounts, savings deposits and interest bearing deposits). By conveying that future short rates were likely to be low, the FOMC placed downward pressure on the expectations components of the yields from longer term bonds by reducing the averages of the expected short term interest rates over the maturities of the bonds.

4. *Increase in the Level of Deposits Covered by Federal Insurance*

From 1980 until the crisis, the per-depositor limit insured at each member bank by the Federal Deposit Insurance Corporation (FDIC) was $\$100,000$. The 1933 Banking Act created the FDIC to restore trust in the U.S. banking system. This was because in the portion of the

[5] The data for figure 3 is available from the FDIC and is provided in the Call Reports.

Great Depression before the FDIC was formed more than one-third of banks failed and bank runs were common. To restore the loss in depositor confidence due to the 2008 crisis and thereby help stabilize the U.S. banking system, from October 3, 2008 to December 31, 2010, Congress temporarily increased the per-depositor limit that was covered by the FDIC insurance fund to $\$250,000$.

There had been a run on deposits at Washington Mutual and, as a result, Wachovia, and increasing the per-depositor insurance limit was designed to guard against similar runs at other banks. Washington Mutual failed on September 26, 2008 following a ten-day run on its deposits and represented a large bank failure during the crisis with assets of \$307 billion. This led to a run on deposits at Wachovia, another large troubled bank, as depositors drew their accounts below the $\$100,000$ insurance limit.

On May 20, 2009 the temporary increase in the per-depositor insurance limit to $\$250,000$ was extended to December 31, 2013, and the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act made this higher limit permanent. The permanent increase in the insurance limit will have led to an increase in deposits, which is in line with the reasonably stable post-crisis upward trends in the levels of non-transaction accounts, savings deposits and interest bearing deposits that we observed in figure 1. The permanent increase in the insurance limit is a part of Dodd-Frank that related to deposits to guard against a repeat of the banking instability in the crisis. There are various other parts of Dodd-Frank that focus on other aspects of banks' activities to prevent such instability in the future. For example, the Volcker Rule was designed to prevent a repeat of the excessive risk taking by banks by preventing banks from using their own accounts for various speculative trading activities that do not benefit their customers.

In contrast to the 2008 crisis leading to some fluctuations in, in particular, the levels of non-transaction accounts and interest bearing deposits, it is evident from figure 1 that there are some deposit types where there has been no such variability over our study period. Changes in the levels of some deposit types have instead evolved steadily over time. Such changes and our reasoning for these changes in depositors' preferences are as follows. First, we can see from panel A in figure 1 that the 2008 crisis marked the end of the gradual upward trend in the level of other transaction and other non-transaction accounts, after which there was a flatlining of this deposit type. It is conceivable that this flatlining is because the crisis prompted depositors to be more conservative about non-traditional deposit types. This would lead to depositors having a greater preference for core transaction and core non-transaction accounts, which is consistent with the levels of both these accounts, and particularly the latter, trending upwards in the post-crisis period (see panel A of figure 1).

Second, in the period covering the crisis and beyond, panel B of figure 1 reveals a non-negligible downward trend in time deposits, which together with the marked upward trend in savings deposits suggests that the crisis prompted a much greater preference for more liquid deposits. Third and finally, it is evident from panel B of figure 1 that there is a diminishing upward trend in savings deposits over the period $2002 - 2007$. This is to be expected as it is in line with the progression of the U.S. economy through the expansion phase of the business cycle (2001:Q4 – 2007:Q3, inclusive), and towards the crisis induced recession phase

(2007:Q4 – 2009:Q2, inclusive).[6]

3 Modeling Framework: Input Distance and Cost Functions, Duality and Estimation

Let $x \in \mathbb{R}^+$ be the set of K inputs, indexed $k = 1, ..., K$, that producers have at their disposal. Now let $y \in \mathbb{R}^+$ be the set of M outputs, indexed $m = 1, ..., M$, that producers use x to produce. As we adopt an input-oriented approach, the production technology is characterized by the input requirement set $I(y) = \{x \in \mathbb{R}^+ : x \textit{ can produce } y\}$. $I(y)$ therefore describes the sets of input vectors that are feasible for each output vector. À la McFadden (1978), we represent the general form of this production technology using the IDF as follows:

$$D_I(y, x) = \max_{\lambda} \left\{ \lambda : \frac{x}{\lambda} \in I(y) \geq 1 \right\}, \tag{1}$$

where the scalar $\lambda \geq 1$ and D_I denotes distance to the IDF. All points on the convex IDF correspond to $\lambda = 1$ and hence $D_I = 1$ and represent minimum radial combinations of input quantities that can be used to produce given output vectors. An IDF has the following five properties (McFadden, 1978): (i) non-decreasing in x, $\partial \ln D_I(y, x)/\partial \ln x_k \equiv ex_k \geq 0$, where ex_k is the kth input elasticity; (ii) non-increasing in y, $\partial \ln D_I(y, x)/\partial \ln y_m \equiv ey_m \leq 0$, where ey_m is the mth output elasticity; (iii) homogeneity of degree one in x, $D_I(y, x/x_k) = D_I(y, x)/x_k$; (iv) concave and continuous in x; (v) $E_I = -\left(\sum_{m=1}^{M} \partial \ln D_I(y, x)/\partial \ln y_m\right)^{-1} \equiv -\left(\sum_{m=1}^{M} ey_m\right)^{-1}$ is the scale elasticity of the IDF representation of the production technology.

The general form of the cost function can be represented as follows:

$$C(y, p) \equiv \min_{x} \{px : D_I(y, x) \geq 1\}, \tag{2}$$

where $p \in \mathbb{R}^+$ is the set of K input prices and $C = \sum_{k=1}^{K} p_k x_k$ is the expenditure on inputs. Accordingly, there is a direct correspondence between the above five properties of $D_I(y, x)$ and the following five properties of $C(y, p)$: (i) non-decreasing in y, $\partial \ln C(y, p)/\partial \ln y_m \equiv ey_m \geq 0$; (ii) non-decreasing in p, $\partial \ln C(y, p)/\partial \ln p_k \equiv ep_k \geq 0$, where ep_k is the kth input price elasticity; (iii) homogeneity of degree one in p, $C(y, p/p_k) = C(y, p)/p_k$; (iv) concave and continuous in p; (v) $E_C = \left(\sum_{m=1}^{M} \partial \ln C(y, p)/\partial \ln y_m\right)^{-1} \equiv \left(\sum_{m=1}^{M} ey_m\right)^{-1}$ is the scale elasticity of the cost function representation of the production technology.

Given the duality between the IDF and the cost function, they are completely symmetric in their treatment of input quantities and input prices conditional on the fixed output vector (Shephard, 1970). The IDF can therefore be recovered from the cost function as follows:

$$D_I(y, x) \equiv \min_{p} \{px : C(y, p) \geq 1\}. \tag{3}$$

Applying Shephard's lemma (Shephard, 1970) to the cost function yields the input demand function for the kth input, X_k:

[6] The dates of these phases of U.S. business cycles are from the National Bureau of Economic Research (https://www.nber.org/cycles.html).

$$X_k = \frac{\partial C(y,p)}{\partial p_k} = \frac{\partial \ln C(y,p)}{\partial \ln p_k}\frac{C(y,p)}{p_k}. \tag{4}$$

The associated cost share equation for the kth input, S_k, is:

$$S_k = \frac{\partial \ln C(y,p)}{\partial \ln p_k}. \tag{5}$$

Consider the general form of the IDF in Eq. 6, a version of which we estimate in the empirical analysis. The dependent variable is $-x_K$, where lower case letters denote logged variables. We obtain this dependent variable by applying property (iii) of an IDF from above and normalizing the other inputs on the right-hand side by the input on the left.

$$-x_{Kit} = \alpha_i + TL_i\left(\widetilde{x}_{it}, y_{it}, t\right) + \gamma_i' z_{it} + \varepsilon_{it}, \tag{6}$$

where

$$TL_i(\widetilde{x}_{it}, y_{it}, t) = \rho_i t + \zeta_i t^2 + \kappa_i'\widetilde{x}_{it} + \eta_i' y_{it} + \frac{1}{2}\widetilde{x}_{it}'\Theta_i\widetilde{x}_{it} + \frac{1}{2}y_{it}'\Gamma_i y_{it} + \widetilde{x}_{it}'\Phi_i y_{it} + \delta_i'\widetilde{x}_{it}t + \psi_i' y_{it}t.$$

In each cross-section there are N units, indexed $i = 1, ..., N$, that operate over T periods, indexed $t = 1, ..., T$, where we consider the typical case that is encountered when using firm level data of large N and small T. α_i is an intercept, which, as is the case for the other parameters in Eq. 6, is for the ith unit. This is because Eq. 6 represents a random coefficients specification, which, as we discuss in more detail further in this section, is well-suited to our very heterogeneous sample of U.S. banks as it yields a richer set of parameter estimates than the fixed parameters from standard fixed and random effects models. $TL_i(\widetilde{x}_{it}, y_{it}, t)$ in Eq. 6 represents the variable returns to scale translog approximation of the log of the IDF production technology. $\widetilde{x}_{it} = x_{it} - x_{Kit}$ denotes the $(1 \times (K-1))$ vector of observations for the normalized logged inputs and y_{it} is the $(1 \times M)$ vector of observations for the logged outputs. t is a time trend and by interacting the outputs and normalized inputs with t technical change is non-neutral. z_{it} is a vector of observations for the variables that shift the IDF production technology and ε_{it} is the idiosyncratic disturbance. ρ_i and ζ_i are regression parameters, κ_i', η_i', δ_i', ψ_i' and γ_i' are vectors of regression parameters, and Θ_i, Γ_i and Φ_i are matrices of the regression parameters θ_i, τ_i and ϕ_i, respectively. It follows from the properties of the translog functional form (Christensen *et al.*, 1973) that Eq. 6 is twice differentiable with respect to a logged output and a normalized logged input. The associated Hessians are symmetric because of the symmetry restrictions that are imposed on Θ_i and Γ_i (e.g., $\tau_{i,1M} = \tau_{i,M1}$).

In our random coefficients model the heterogeneity between the banks is treated as stochastic variation. Our model has a rich specification that permits two levels of latent variables pertaining to a fixed component across all banks and a heterogenous random component for each bank. With such a specification each bank has its own IDF with its own set of parameters to better reflect the extent of the heterogeneity across U.S. banks. It is possible to estimate a full random coefficients model, as specified in Eq. 6, where each parameter is estimated for each bank, or a partial random coefficients model, where the set of parameters for each bank is a mix of fixed parameters across all banks and parameters that are estimated for each bank. When using very large data sets to estimate models with a quite a large number of variables, as is the case in this paper, it is more practical to estimate a partial random coefficients model, otherwise estimation time becomes infeasible. As we are interested in deposit type substitution/complementarity, we therefore estimate an IDF for each bank with a set of random slopes for the first order deposit types, ξ_i, to reflect the heterogeneity in the banks' technologies. $\xi_i \subset \kappa_i$ as κ_i also contains fixed parameter estimates for non-deposit inputs. ξ_i is distributed according to the following $(K-L)$ variate normal distribution, where K is the total number of inputs and L is the number of non-deposit inputs:

$$\xi_i \sim N(\bar{\xi}, \Omega), \quad i = 1, ..., N. \tag{7}$$

In Eq. 7 $\bar{\xi}$ is the $((K-L) \times 1)$ vector of parameter means and Ω is the $((K-L) \times (K-L))$ positive definite covariance matrix. The model assumes that $\left(\xi_i | \bar{\xi}, \Omega\right)$ and ε_{it} are i.i.d. In the empirical analysis we provide further justification for limiting the random coefficients modeling to the first order deposit types. Note that we only touch on the approach to the random coefficients modeling here as it is a standard approach. For a more detailed discussion of random coefficients modeling see, among others, Cuthbertson *et al.* (1992).

4 Input Elasticities of Substitution and Complementarity from an Input Distance Function

Turning now to a presentation of the six elasticities of substitution and complementarity that we compute from a fitted IDF. For a synthesis of the literature on elasticities of substitution and complementarity with reference to computation of the elasticities from a cost function see Stern (2011). Our presentation of the elasticities, which also provides an insight into the evolution of the literature, is in terms of two inputs x_* and $x_\circ$ from the input vector x.

1. *Symmetric Antonelli Elasticity of Complementarity (AEC)*: Blackorby and Russell (1981) derive this elasticity and refer to it as the true dual of the AES under non-constant returns to scale. Kim (2000), on the other hand, refers to this elasticity as the AEC, which is the terminology we use here.[7] To measure the response to a change in the input quantity x_* the formula for the AEC is as follows.

$$AEC_{*\circ} = \frac{D_I(y,x)\frac{\partial^2 D_I(y,x)}{\partial x_* \partial x_\circ}}{\frac{\partial D_I(y,x)}{\partial x_*}\frac{\partial D_I(y,x)}{\partial x_\circ}} = \frac{1}{S_*}\frac{\partial \ln P_\circ(y,x)}{\partial \ln x_*}, \tag{8}$$

where applying Shephard's lemma to the IDF yields the inverse input demand function for input $\circ$, $P_\circ(y,x) = \partial D_I(y,x)/\partial x_\circ$, which measures the shadow price of the input. From the IDF we also obtain the cost share equation for input $*$, $S_* = \partial \ln D_I(y,x)/\partial \ln x_*$.

[7] Kim (2000) attributes the AEC to Antonelli (1886) as it involves using the Antonelli substitution matrix, which is the matrix of second order partial derivatives of a distance function (Deaton, 1979).

In our empirical analysis we use the fitted IDF to compute the $AEC_{*\circ}$ as follows.

$$AEC_{*\circ} = \frac{\theta_{i,*\circ} + S_{i,*}S_{i,\circ}}{S_{i,*}S_{i,\circ}}, \tag{9}$$

where $\theta_{i,*\circ}$ is the relevant element of Θ_i from $TL_i(x_{it}, y_{it}, t)$ in Eq. 6. At the sample mean $S_{i,*} = \kappa_{i,*}$ and $S_{i,\circ} = \kappa_{i,\circ}$, where $\kappa_{i,*}$ and $\kappa_{i,\circ}$ are the relevant elements of κ_i' from $TL_i(x_{it}, y_{it}, t)$. This is because we use mean adjusted data and, as a result, the terms in the partial derivatives of Eq. 6 that relate to the quadratic and interaction terms in $TL_i(x_{it}, y_{it}, t)$ are zero at the sample mean.

2. *Symmetric Allen-Uzawa Elasticity of Substitution (AES)*: The AES is jointly due to Allen (1934; 1938), who shows how to compute the AES from a production function (i.e., the primal AES), and Uzawa (1962), who shows how to calculate the AES from a cost function (i.e., the dual AES). Given the duality between the cost function and the IDF we compute the dual AES in our empirical analysis. The formula for the dual AES to measure the response to a change in input price p_* is given in Eq. 10. This formula is valid not just for a single output, which is how Allen (1938) presented the primal AES, but also multiple outputs.

$$AES_{*\circ} = \frac{C(y,p)\frac{\partial^2 C(y,p)}{\partial p_* \partial p_\circ}}{\frac{\partial C(y,p)}{\partial p_*}\frac{\partial C(y,p)}{\partial p_\circ}} = \frac{1}{S_*}\frac{\partial \ln X_\circ(y,p)}{\partial \ln p_*}. \tag{10}$$

To obtain the $AES_{*\circ}$ in our empirical analysis we draw on Broer (2004) by obtaining the matrix of AESs, $\mathbf{AES}_{*\circ}$, from the matrix of AECs, $\mathbf{AEC}_{*\circ}$, as follows.

$$\begin{bmatrix} \mathbf{AES}_{*\circ} & \iota \\ \iota' & 0 \end{bmatrix}^{-1} = \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ 0 & \ddots & \vdots & \vdots \\ \vdots & \cdots & S_K & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{AEC}_{*\circ} & \iota \\ \iota' & 0 \end{bmatrix} \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ 0 & \ddots & \vdots & \vdots \\ \vdots & \cdots & S_K & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix}, \tag{11}$$

where ι is a column vector of ones and the elements of $\mathbf{AEC}_{*\circ}$ and S_k are computed as described above (see Eq. 9).

3. *Asymmetric Morishima Elasticity of Complementarity (MEC)*: The formula for the $MEC_{*\circ}$ from Blackorby and Russell (1981) and Kim (2000) to measure the response to a change in input quantity x_* is:

$$MEC_{*\circ} = \frac{\partial \ln\left(\frac{\partial D_I(y,x)}{\partial x_*} / \frac{\partial D_I(y,x)}{\partial x_\circ}\right)}{\partial \ln(x_\circ / x_*)} \tag{12}$$

$$= \frac{\partial \ln P_\circ(y,x)}{\partial \ln x_*} - \frac{\partial \ln P_*(y,x)}{\partial \ln x_*}. \tag{13}$$

From Eq. 13 we can see that the MEC is the difference between two input quantity elasticities which are in terms of two inverse input demand functions. The $MEC_{*\circ}$ measures the optimal change in the shadow input price ratio when x_* changes in the fixed input quantity ratio and $x_\circ$ is allowed to adjust optimally by holding the price of input $\circ$ constant. In our empirical analysis we calculate the $MEC_{*\circ}$ using Eq. 13. This involves obtaining equations from Eq. 8 for $AEC_{*\circ}S_*$ and $AEC_{**}S_*$ and substituting in for the two terms on the right-hand side of Eq. 13, respectively.

4. *Asymmetric Morishima Elasticity of Substitution (MES)*: The MES dates back to Morishima (1967) and the formula for the MES in Blackorby and Russell (1975) for the optimal response to a change in input price p_* is:

$$MES_{*\circ} = \frac{\partial \ln \left(\frac{\partial C(y,p)}{\partial p_*} / \frac{\partial C(y,p)}{\partial p_\circ} \right)}{\partial \ln \left(p_\circ / p_* \right)}. \tag{14}$$

Following Blackorby and Russell (1989) Eq. 14 for a change in p_* can be rewritten as:

$$\begin{aligned} MES_{*\circ} &= \frac{p_* \left(\frac{\partial^2 C(y,p)}{\partial p_* \partial p_\circ} \frac{\partial C(y,p)}{\partial p_*} - \frac{\partial^2 C(y,p)}{\partial p_*^2} \frac{\partial C(y,p)}{\partial p_\circ} \right)}{\frac{\partial C(y,p)}{\partial p_*} \frac{\partial C(y,p)}{\partial p_\circ}} \\ &= \frac{\partial \ln X_\circ (y,p)}{\partial \ln p_*} - \frac{\partial \ln X_* (y,p)}{\partial \ln p_*}, \end{aligned} \tag{15}$$

where $X_\circ (y,p)$ and $X_* (y,p)$ are factor input demand functions from Eq. 4. To compute the $MES_{*\circ}$ in our empirical analysis we use the corresponding approach to calculate the $MEC_{*\circ}$. This involves using Eq. 10 to obtain equations for $AES_{*\circ}S_*$ and $AES_{**}S_*$, and these equations are then substituted into Eq. 15.

5. *Symmetric Shadow Elasticity of Complementarity (SEC)*: The corresponding primal elasticity of complementary to the dual SES, which is the final elasticity we present, is the SEC (Stern, 2010). The SEC measures the optimal response of the shadow input price ratio to a change in the ratio of two input quantities, holding any other input quantities, the quantity of output and distance constant. As the SEC refers to movements along the input distance frontier it has the appealing feature that it measures input substitution when production is technically efficient. In contrast, the input quantity ratio is fixed for the AEC and the MEC so it is not possible for one input quantity to change holding output constant unless distance changes. The AEC and MEC do not therefore measure input substitution along the input distance frontier. The formula for the SEC is:

$$\begin{aligned} SEC_{*\circ} &= \frac{\partial \ln \left(\frac{\partial D_I(y,x)}{\partial x_*} / \frac{\partial D_I(y,x)}{\partial x_\circ} \right)}{\partial \ln \left(x_\circ / x_* \right)} | D_I \\ &= \frac{- \frac{\partial^2 D_I(y,x)/\partial x_*^2}{\frac{\partial D_I(y,x)}{\partial x_*} \frac{\partial D_I(y,x)}{\partial x_*}} + 2 \frac{\partial^2 D_I(y,x)/\partial x_* \partial x_\circ}{\frac{\partial D_I(y,x)}{\partial x_*} \frac{\partial D_I(y,x)}{\partial x_\circ}} - \frac{\partial^2 D_I(y,x)/\partial x_\circ^2}{\frac{\partial D_I(y,x)}{\partial x_\circ} \frac{\partial D_I(y,x)}{\partial x_\circ}}}{\frac{1}{(\partial D_I(y,x)/\partial x_*) x_*} + \frac{1}{(\partial D_I(y,x)/\partial x_\circ) x_\circ}}. \end{aligned} \tag{16}$$

As in Eq. 17, the SEC can be shown to be the share-weighted average of three AECs (Stern, 2010), which is the result we use to calculate the SEC in our empirical analysis. To obtain Eq. 17: (i) In Eq. 8 for the AEC_{**}, $AEC_{*\circ}$ and $AEC_{\circ\circ}$ we set $D_I(y,x) = 1$ because input substitution occurs along the input distance frontier. We then substitute into the numerator of Eq. 16 to obtain $-AEC_{**}+2AEC_{*\circ}-AEC_{\circ\circ}$. (ii) In the inverse demand functions for inputs $*$ and $\circ$ from the IDF (e.g., $P_\circ = \partial D_I(y,x)/\partial x_\circ = (\partial \ln D_I(y,x)/\partial \ln x_\circ)\, D_I(y,x)/x_\circ$) we set $D_I(y,x) = 1$ and drawing on the cost share equations from the IDF (e.g., $S_\circ = \partial \ln D(y,x)/\partial \ln x_\circ$) we rewrite and substitute in for each term in the denominator of Eq. 16 (e.g., $\frac{1}{S_\circ} = \frac{1}{(\partial D_I(y,x)/\partial x_\circ)x_\circ}$).

$$\begin{aligned} SEC_{*\circ} &= \frac{1}{\frac{S_\circ}{S_* S_\circ} + \frac{S_*}{S_* S_\circ}} \left(-AEC_{**} + 2AEC_{*\circ} - AEC_{\circ\circ}\right) \\ &= \frac{S_* S_\circ}{S_* + S_\circ} \left(-AEC_{**} + 2AEC_{*\circ} - AEC_{\circ\circ}\right). \end{aligned} \tag{17}$$

6. *Symmetric Shadow Elasticity of Substitution* (*SES*): McFadden (1963) derived the SES which Mundlak (1968) observes is the MES when cost is held constant. Whereas the MES is asymmetric the SES is symmetric because of the constant cost requirement. Since the SEC measures input substitution along the input distance frontier and the SES measures input substitution along the isocost curve, it is clear that the SEC is the dual of the SES. The formula for the SES is as follows.

$$\begin{aligned} SES_{*\circ} &= \frac{\partial \ln \left(\frac{\partial C(y,p)}{\partial p_*} / \frac{\partial C(y,p)}{\partial p_\circ} \right)}{\partial \ln \left(p_\circ / p_*\right)} |C \\ &= \frac{-\frac{\partial^2 C(y,p)/\partial p_*^2}{\frac{\partial C(y,p)}{\partial p_*}\frac{\partial C(y,p)}{\partial p_*}} + 2\frac{\partial^2 C(y,p)/\partial p_* \partial p_\circ}{\frac{\partial C(y,p)}{\partial p_*}\frac{\partial C(y,p)}{\partial p_\circ}} - \frac{\partial^2 C(y,p)/\partial p_\circ^2}{\frac{\partial C(y,p)}{\partial p_\circ}\frac{\partial C(y,p)}{\partial p_\circ}}}{\frac{1}{(\partial C(y,p)/\partial p_*)p_*} + \frac{1}{(\partial C(y,p)/\partial p_\circ)p_\circ}}. \end{aligned} \tag{18}$$

Analogous to the above representation of the SEC, the SES can be expressed as the following share-weighted average of three AESs, which is the result we use to compute the SES in our empirical analysis. In brief given the analogous nature of the SES, we obtain Eq. 19 by first setting $C(y,p) = 1$ in Eq. 10 for the AES_{**}, $AES_{*\circ}$ and $AES_{\circ\circ}$, and we then substitute into the numerator of Eq. 18. We next set $C(y,p) = 1$ in the demand functions for inputs $*$ and $\circ$ and using the cost share equations we rearrange and substitute in for each term in the denominator of Eq. 18.

$$SES_{*\circ} = \frac{S_* S_\circ}{S_* + S_\circ} \left(-AES_{**} + 2AES_{*\circ} - AES_{\circ\circ}\right). \tag{19}$$

5 Empirical Analysis

5.1 Data, Variables and Model Specifications

We estimate a number of specifications of the IDF for insured U.S. commercial banks for two time periods using rich annual year-end unbalanced panel data. The first time period is $1992-2007$ and the second is $2008-2015$. Following Vazquez and Federico (2015), who refer to $2001-2007$ as capturing the evolution of bank financial conditions in the run up to the crisis and $2008-2009$ as the crisis period, we interpret our first sample as a pre-crisis period and we refer to our second as a period that covers the crisis and beyond. Looking ahead to our fitted models, testing whole sets of parameters from the models for the two periods against one another using a Wald test justifies splitting the entire sample. See the presentation and analysis of our fitted IDFs in subsection 5.2 for a discussion of these test results.

We omit each bank-year from the two data sets where there was a missing observation for a variable. The resulting data sets we use for the periods $1992 - 2007$ and $2008 - 2015$ are both large, as they comprise $127,076$ bank-year observations and $44,504$ bank-year observations, respectively. All the data for the variables was either extracted directly from the Reports of Condition and Income (i.e., the Call Reports) of the Federal Reserve System, which we obtain from the Federal Deposit Insurance Corporation (FDIC), or was constructed by the authors using data from this source. All monetary volumes are deflated to 2005 prices using the consumer price index.

To make appropriate comparisons we use the same set of variables to estimate the IDF for each time period. The inputs and outputs in our IDF specifications are based on the Sealey and Lindley (1977) intermediation approach to banking. We therefore assume, first, that banks use the savings of consumers and firms to make investments and, second, that banks seek to minimize the cost associated with the production of their outputs. In Table 1 we describe the variables we use to estimate the models and provide summary statistics for these variables for both sample periods. For each sample period we estimate three model specifications using three outputs ($y_1 - y_3$), which reflect the lending and non-lending activities of the banks. These three model specifications also have nine z variables that shift the IDF production technology ($z_1 - z_9$). Model specifications 1 and 2 have five inputs and model specification 3 has four inputs. All three model specifications include as inputs, the number of full-time equivalent employees as the labor input, x_1, and premises and fixed assets, x_2. The remaining inputs in the three model specifications represent different disaggregations of total deposits. For example, model specification 1 disaggregates total deposits into transaction accounts, non-transaction accounts and other transaction and other non-transaction accounts.

[Insert table 1 about here]

From inspecting the mean levels of the deposit types in table 1 we can see that there were large increases between the periods $1992 - 2007$ and $2008 - 2015$. To illustrate, across the eight deposit types we consider, the smallest percentage increase is the 33% rise in mean total time deposits, while the largest percentage increase is the huge 218% rise in mean total savings deposits.

Turning next to a discussion of the fitted IDFs, where all the inputs and outputs are logged. We then mean adjust the inputs and outputs and the time trend so the associated first order parameters can be interpreted as elasticities at the sample mean.

5.2 Discussion of the Estimated Input Distance Functions

The estimated IDFs for model specifications $1 - 3$ for the period before the crisis $(1992 - 2007)$ and for the period covering the crisis and beyond $(2008 - 2015)$ are presented in tables $2 - 4$. $-x_1$ is the dependent variable for the reported IDFs and is also therefore the normalizing input for these models. To recap, we account for the heterogeneity across the banks via a set of random intercepts and via a set of random slopes for a first order deposit type as we are primarily interested in deposit type substitution/complementarity. All the other parameters are the usual fixed estimates. Furthermore, from a practical perspective we only estimate random slopes for the first order deposit types rather than for all the variables in the models so that model run time does not become excessive.[8] For each first order deposit type we obtain a slope parameter for each bank so to facilitate interpretation we report an average of these parameters across the banks. We compute the associated t-statistic by dividing this average parameter by the standard deviation of the parameters for the individual banks.

[Insert tables $2-4$ about here]

For each bank the intercept and slope for each deposit type are made up of a fixed component and a heterogeneous random component. In tables $2-4$ the relevant standard deviation indicates whether there is significant variation across the banks between the random components of the coefficients on a first order deposit type. This variation across the banks in the random components of the coefficients on a first order deposit type would be overlooked by a fixed parameter model, whereas the widespread significant standard deviations for first order deposit types in tables $2-4$ provide support for random parameter modeling of these variables. Moreover, fixed parameter models implicitly allow correlation between the intercept and the regressors, but the model output from a random parameters model is more explicit about this correlation. To illustrate, the correlations in tables $2-4$ indicate that there are a number of cases where there is significant correlation between the random components of the intercept and a first order deposit type.

To ascertain whether the fitted models support splitting the entire sample, a Wald test is used to test the null hypothesis of equality of the two sets of parameters for the pre-crisis period and the period covering the crisis and beyond. For all three model specifications we reject the null that the two sets of parameters are equal at the 0.1% level, which supports estimating separate IDFs for $1992-2007$ and $2008-2015$.[9]

As expected the three fitted model specifications for both sample periods in tables $2-4$ all yield negative output elasticities and positive input elasticities at the sample mean. We can therefore conclude that at the sample mean all the fitted models satisfy the monotonicity property of the translog IDF. From the estimates of model specifications $1-3$ for $1992-2007$ we observe evidence of moderate increasing returns to scale that lie within the narrow band of $1.07-1.09$. Even though we find evidence of only moderate increasing returns Wald tests reveal that in each case the returns are significantly different from 1 at the 0.1% level. This is because the variances and covariances of the first order output parameters are particularly small. This evidence of moderate increasing returns is consistent with a good proportion of the findings for pre-crisis samples from two seminal studies of returns to scale in U.S. banking (Wheelock and Wilson, 2001; 2012).

[8] With such large data sets for our sample periods and the large number of variables in each model, even when we only estimate random slopes for the first order deposit types estimating a single model can take up to four hours.

[9] Specifically, the three Wald tests clearly reject the null as the χ^2 test statistics are extremely large as they range from $12,106-17,124$.

Interestingly, our three fitted model specifications for $2008-2015$ all suggest that there are larger increasing returns to scale in our second sample period. Our returns to scale estimates for $2008-2015$ lie within the narrow band of $1.19-1.21$ and in each case are significantly different from 1 at the 0.1% level. This suggests for the sample average bank that the same proportionate increase in inputs in both sample periods would lead to a much bigger increase in bank size in the latter period. The principal reason why we observe larger increasing returns for our second sample period is because for each model specification the coefficient on total securities (y_2) is lower for the $2008-2015$ period than $1992-2007$.

The first order time trend parameters from the three model specifications for the $1992-2007$ sample period are all positive. These time trend parameters are of the order $0.005-0.007$ and are all significant at the 0.1% level. For the sample average bank this suggests that, on average, the IDF shifts up annually by at least 0.5% due to technical progress. A positive estimate of the first order time trend parameter is in line with our expectations and suggests that in this respect $1992-2007$ is a typical type of period. This is because annual technical progress is in line with the prediction from production theory and is consistent with technical innovations in the U.S. banking industry during this period, such as further formats for debit card transactions, the introduction of online banking and asset securitization (Llewellyn, 2009; Frame and White, 2010).

The first order time trend parameters from the three model specifications for the $2008-2015$ sample period range from $-0.007-(-0.005)$ and are all significant at the 0.1% level. These negative estimates are at odds with production theory and inconsistent with technical innovations in the industry over this period. Such innovations include enhanced automated credit scoring and more widespread use of fintech technologies, e.g., the application of artificial intelligence and machine learning in lending activities for marketing and account monitoring purposes (Frame *et al.*, 2018; Thakor, 2019). In this respect these estimates suggest that $2008-2015$ is an atypical period, which of course is particularly true for the first portion of this period. For $2008-2015$, we posit that we obtain negative first order time trend parameters because the negative effect of the deepening of the financial crisis on technical change more than offset the positive effect of the technical innovations during this period.

We conclude our discussion of the fitted models by focusing on the salient results for the z variables. With the exception of the bank asset market share (MS) variable, for each model specification, the signs of the coefficients on the z variables that have a large and significant effect remain unchanged between the two sample periods. Recall that the dependent variable for all the fitted models is the negative logged labor input ($-x_1$). For all three model specifications the MS variable switches from having a large negative effect on the labor input over the period $1992-2007$ to having a large positive effect in the $2008-2015$ sample. Although it is clear from figure 1 that the financial crisis is associated with changes in the levels of some deposit types, we do not attribute the change in the effect of MS on the labor input to the crisis. Instead we posit that the different effects of MS in our two sample periods reflects the declining role of labor in U.S. bank production over time. This is because in our latter sample period electronic banking is much more prominent and following an increase in a bank's MS it would be better placed to fund investment in electronic banking and, as a result, reduce its labor input. In contrast, during our earlier sample period labor had a bigger role in bank production and following an increase in a bank's MS it would be in a better position to finance expansion by increasing its labor input.

5.3 Discussion of Deposit Type Substitution and Complementarity

For model specifications $1-3$ for the periods $1992-2007$ and $2008-2015$, we compute at the sample mean from our fitted IDFs the six elasticities of substitution and complementarity we presented in section 4 (AEC; SEC; MEC; AES; SES; MES). For pairs of deposit types these six elasticities are presented in tables $5-7$ and for the elasticities of complementarity we compute the standard errors using the delta method.[10]

As the theoretical literature on elasticities of substitution and complementarity is made up of a series of elasticities that measure different relationships, we adopt a logical two-part structure for our discussion that is based on a systematic two-stage bank decision-making process on deposit type substitution/complementarity. In the first part we discuss, in particular, our findings for the AEC and AES, as well as our MEC and MES results. We discuss these elasticity results in the first part because they can be used in the first stage of the bank decision-making process to inform which deposits are substitutes/complements. Moreover, in the first part of the discussion we place the emphasis on the AEC (and AES) results to indicate if two deposit types are q substitutes/complements (p substitutes/complements). This is because, although the MES and the MEC are appealing because they are asymmetric, as Stern (2011) notes, when the production technology is characterized by more that two inputs, the MEC (MES) should not be used to classify if two inputs are q substitutes/complements (p substitutes/complements).[11] In all three of our model specifications there are more than two deposit types, which is why the AEC and AES are more relevant to our empirical setting.

Given a bank's knowledge from the first stage of the decision-making process, the second stage of this process relates to how viable it is to substitute between deposit types. In the second part of the discussion we therefore provide some analysis of our SEC and SES results, as these elasticities measure the degree of difficulty of input substitution/complementarity. Given the paucity of studies that consider elasticities of substitution/complementarity of deposit types, we place the emphasis on the first part of our discussion, which informs the first stage of the decision-making process, as this is the logical approach to develop further this small body of literature.

[Insert tables $5-7$ about here]

Table 5 reveals for the period before the crisis and the period covering the crisis and beyond that the AECs for each pair of deposit types from model specification 1 are positive and significant at the 1% level or lower (i.e., pairwise combinations of transaction accounts,

[10] The matrix inversion to compute the AES from the AEC (see Eq. 11) precludes calculating the standard error of the AES using the delta method. This is also the case for the SES and the MES as they are calculated from the AES. This could be addressed by computing the standard errors for the dual elasticities of substitution by bootstrapping, although this is outside the scope of this paper.

[11] We still report the MEC and MES estimates for two reasons. First, to demonstrate how they should be calculated in the two input case. Second, to appreciate any differences in the results on deposit type substitution/complementarity when using the more appropriate AEC and AES for our case with more than two inputs.

non-transaction accounts, and other transaction and other non-transaction accounts (D1-D3, respectively)). This indicates that each pair of deposit types in this model specification are significant q complements in both sample periods. The implication is that the small changes we observe in panel A of figure 1 in the levels of these deposit types in the period covering the crisis and beyond were not sufficient to change the q complements classification for pairs of these deposit types. These small changes in deposit levels are the temporary drop in transaction accounts due to the crisis, and over the crisis period and beyond the flatlining of non-transaction accounts and the slow rise in other transaction and other non-transaction accounts.

In contrast to our results from model specification 1, from model specification 2 there are some cases where the q substitutes/complements results differ between the two sample periods. Table 6 reports three such findings. (i) The AECs for savings deposits (D2) and other deposits (D3) for $1992-2007$ and $2008-2015$ are significant at the 0.1% level and indicate q complementarity and q substitutability, respectively. (ii) The time deposits (D1) and D3 AECs for the two sample periods have different signs, but neither is significant. (iii) The D1 and D2 AECs for the two sample periods are positive and significant indicating q complementarity, but whereas the AEC for $1992-2007$ is significant at the 0.1% level, it is only significant at the 5% level for $2008-2015$. Of these three findings the most noteworthy is (i) and to a lesser extent (iii). (i) is in line with the divergence of savings deposits and other deposits that we observe from 2008 onwards in panel B of figure 1. This is due over this period to the steeper upward trend in savings deposits and a fairly constant level of other deposits. (iii) is consistent with the change in the relationship between time deposits and savings deposits that we observe from 2008 onwards in panel B of figure 1. This is due to from 2008 the steady declining trend in time deposits and the steeper upward trend in saving deposits. Whether the trends in these two deposit types from 2008 have continued beyond the end of our study period and have led to these deposits becoming q substitutes is an area for future research.

Interestingly, for the only pair of deposit types in model specification 3 (non-interest bearing and interest bearing deposits), it is evident from Table 7 that the AEC for $1992-2007$ is close to zero and not significant, whereas for $2008-2015$ it is negative and significant at the 0.1% level indicating that these deposits types are q substitutes. This change in the relationship between these deposit types is consistent with the changes from 2008 onwards in the levels of these deposits in panel C of figure 1. To illustrate, non-interest bearing deposits go from being fairly constant up to 2008 to being on a clear downward trend from thereon, whereas interest bearing deposits, following some crisis induced fluctuations, revert to a path that resembles a continuation of its steady pre-crisis upward trend. In terms of the economic intuition that may explain these changes in the levels of these deposit types and why for $2008-2015$ they are q substitutes, it may be because in the uncertain times during the crisis and beyond, depositors had a greater preference for liquid non-interest bearing deposits over more illiquid interest bearing accounts.

Frondel and Schmidt (2002) note that when the MES is incorrectly applied to cases where there are more than two inputs, the MES tends to classify inputs as p substitutes because the own input price elasticity tends to be greater in absolute value than the cross price elasticities. In line with this, we find that the MES is positive for every pair of deposit types, but there is no evidence to suggest that this classification of each pair of deposit types as p substitutes is erroneous because all the AESs in tables $5-7$ are also positive. Applying this to the case of the MEC from an IDF, from the duality of cost and input distance functions, when there are more than two inputs we should observe that the MEC from an IDF tends to classify inputs as q complements. Our results exclusively support this because for every pair of deposit types we find that the MEC is positive. In contrast to our MES and AES results, however, this does lead to some cases where the MEC would appear to incorrectly classify two deposit types as q complements, while the AEC indicates that they are q substitutes. For example, as we noted above for savings deposits and other deposits for $2008-2015$, the significant AEC indicates that these deposit types are q substitutes.

Having discussed the q and p substitutes/complements classifications of pairs of deposit types, we now focus on the changes in the magnitudes of the elasticities between the two sample periods. To this end, in figures 4 and 5 we present for the two sample periods radar diagrams for the elasticities for model specifications 1 and 2.[12] In these figures the blue radars relate to the elasticities for $1992-2007$ and the red radars relate to the elasticities for $2008-2015$. From figure 4 we can see for model specification 1 that the AEC (AES) for each pair of deposit types is larger (smaller) in magnitude for $1992-2007$, vis-à-vis $2008-2015$. This is also the case for model specification 2, with the exception of the AEC and AES for time deposits and other deposits. Consistent with these results for time deposits and other deposits, for model specification 3 we can see from table 7 that the AEC (AES) for interest bearing and non-interest bearing deposits is smaller (larger) for $1992-2007$ than we observe for $2008-2015$.

[Insert figures 4 and 5 about here]

Building on figures 4 and 5, in table 8 we report z-scores for pairwise one-tailed tests of elasticities of complementarity from a $2008-2015$ model against the corresponding elasticity from the $1992-2007$ model. For an AEC that is larger or smaller for $2008-2015$ than we observe for $1992-2007$, table 8 reveals that it is significantly larger or smaller at the 5% level or lower, with the exception of one AEC from model specification 1 (between transaction accounts and other transaction and other non-transaction accounts). For example, the AEC from model specification 2 for time deposits and savings deposits for $1992-2007$ is significantly larger than for $2008-2015$. This indicates that, although these two deposit types are significant q complements in both sample periods, the degree of q complementarity is significantly less in the latter period. This finding is consistent with the change in the relationship between time deposits and savings deposits that we observed above from 2008 onwards due to the steady declining trend in time deposits and the steeper upward trend in savings deposits.

[Insert table 8 about here]

We have discussed how the elasticities we have analyzed thus far can inform the first stage of a bank decision-making process on deposit type substitution/complementarity by indicating

[12] We suggest that radar diagrams of elasticities of substitution and complementarity are particularly useful to compare several elasticity estimates. Model specification 3 comprises just two deposit types which is insufficient to construct a radar diagram of the deposit elasticities. In this situation it is simple to compare the elasticities by eyeballing the estimates.

whether each pair of deposit types are q and p substitutes/complements. Given the bank's knowledge from the first stage of this decision-making process, in the second stage of the process it is perfectly reasonable for banks to consider the degree of difficulty of substitution/complementarity between a pair of deposit types. The degree of difficulty associated with q and p substitution/complementarity between a pair of deposit types relates to the magnitudes of the SEC and SES, respectively. Tables $5 - 7$ indicate for every pair of deposit types for both sample periods that the SEC is positive, as theory requires, less than 1 and significant at the 0.1% level. As all the SECs are less than 1 this suggests that there is limited q substitution/complementarity possibilities between the pairs of deposit types. For every pair of deposit types for both sample periods, tables $5 - 7$ also reveal that the SES is positive and greater than 1, which indicates that there is plenty of scope for p substitution/complementarity.

We would expect there to be plenty of scope for p substitution/complementarity between a pair of deposit types because the relationship between the price of a deposit type, which is the rate of interest that a bank pays on the deposit account, and the quantity of the deposit is well-defined from microeconomic theory. The quantity of a deposit type will therefore be sensitive to a change in its price. It is in turn reasonable to think that the quantity of a deposit type will be sensitive to a change in the price of another deposit type. In contrast, it is not surprising we find that there is limited q substitution/complementarity possibilities between the pairs of deposit types because a change in the quantity of a deposit type may not change the deposit type's marginal product and the marginal products of other deposit types. The reason is because if, for example, the quantity of a deposit type increases at a bank, it does not necessarily follow that this will lead to an increase in one or more of the bank's outputs (e.g., loans), and that it will also impact the relationships between the bank's other deposit types and its outputs. The bank may not use the increase in this input to increase its outputs and could put the increase in the input to an alternative use to aid its financial condition, e.g., increase its reserves at the Fed. We expand on this further in the next section where we conclude by putting into context some of our salient findings on deposit type substitution and complementarity by describing some general banking situations that fit with such findings.

6 Contextual Summary of the Salient Empirical Findings

Figure 1 suggests that the relationships between the levels of some deposit types differ between the pre-crisis period and the period covering the crisis and beyond. The approach we adopt in this paper to quantify any crisis induced changes in the relationships between pairs of deposit types is to analyze if there has been changes in their substitutability/complementarity. It is useful for banks to have such information because deposits are banks' principal source of funding for their lending activities. To indicate how such information may feature in a bank's decision-making, we suggest a logical two-stage bank decision-making process on deposit type substitution/complementarity. In the first stage we suggest that banks may consider whether pairs of deposit types are q and p substitutes/complements. Given this knowledge from the first stage, in the second stage of the process we suggest that banks may consider the degree of difficulty of q and p substitution/complementarity between pairs of deposit types. The two key general findings from our empirical analysis on the substitutability/complementarity of pairs of deposit types in the context of banking situations that fit with these findings are as follows.

1. We only find some evidence, rather than widespread evidence, of changes in the q substitutes/complements classifications of pairs of deposit types between the pre-crisis period and the period covering the crisis and beyond. Given the crisis was a watershed for the U.S. banking industry, this evidence suggests that the q substitutes/complements classification of a pair of deposits types may only change in response to a major development in the industry. Since such developments do not occur regularly, the changes in the q substitutes/complements classifications we discussed in the previous section are likely to represent long-term changes in depositors' preferences between deposit types.

2. In the final point in the previous section, we noted that it is not surprising we find that there is limited q substitution/complementarity possibilities between the pairs of deposit types. This is because a change in the quantity of a deposit type may not change its own marginal product and the marginal products of other deposit types. One reason we gave for this was because if, for example, the quantity of a deposit type increases at a bank, the bank may not choose to use the increase in this input to increase its outputs. It may instead put the increase in the input to an alternative use to aid its financial condition by increasing its capital. Another reason why we may observe limited q substitution/complementarity possibilities between pairs of deposit types is because a change in the quantity of a deposit type at a bank may not be sufficient on its own to change its impact, and the impacts of other deposit types, on the levels of the bank's aggregate outputs in our models. Instead a bank may use the aggregate level of its deposits, as opposed to the levels of deposit categories, to inform decisions about the aggregate levels of its outputs. If this is the case, it raises the issue why we find that a number of pairs of deposit types are q complements in one or both sample periods (e.g., transaction accounts and non-transaction accounts in both sample periods). We suggest it is because changes in economic conditions may have a similar impact on a pair of deposit types, as opposed to the deposit types being directly related to one another. Even if a pair of deposit types are indirectly related, the information that our analysis provides on which pairs of deposit types are q complements can be useful to banks in the strategic management of their deposit portfolios.

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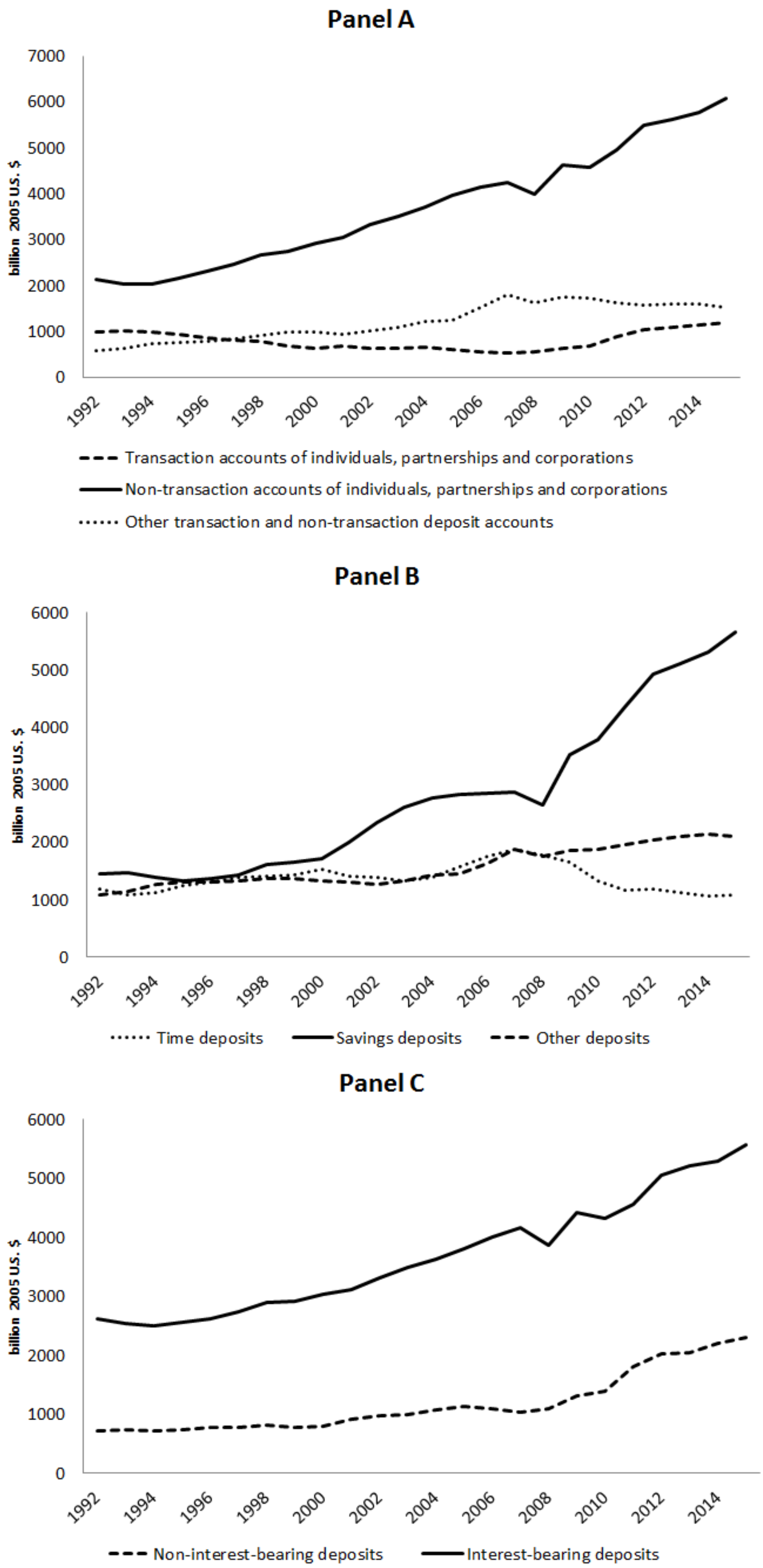

Figure 1: Different disaggregations of annual real deposits in the U.S. banking system

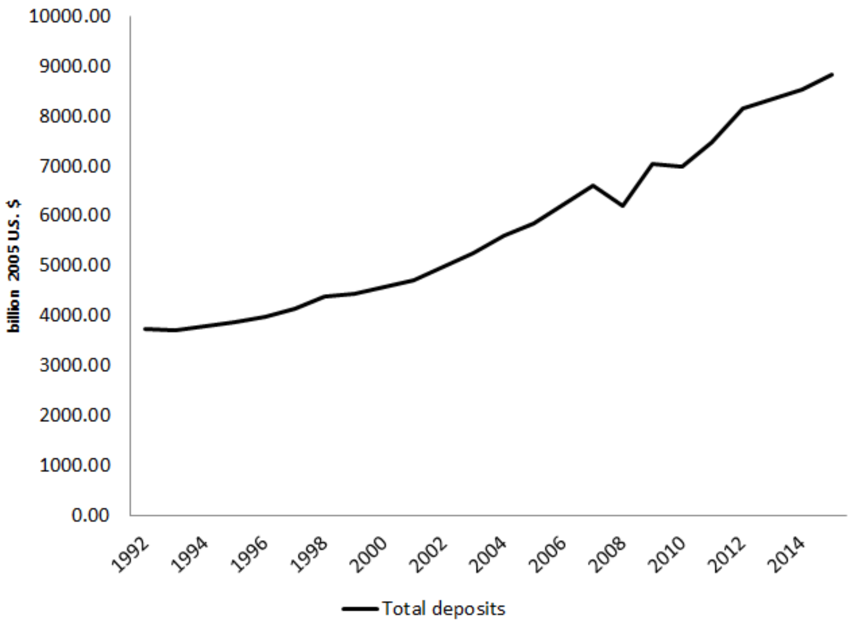

Figure 2: Annual real total deposits in the U.S. banking system

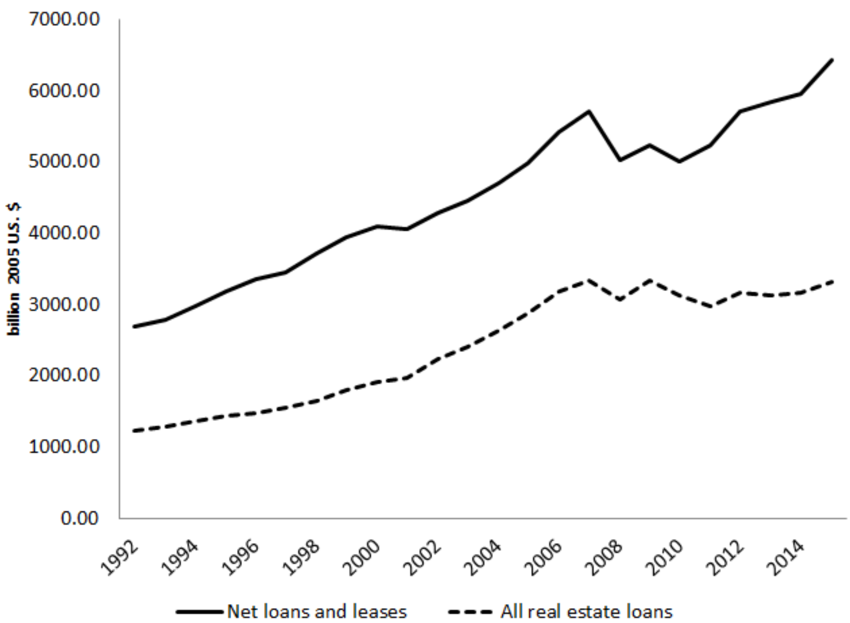

Figure 3: Selected annual real loans in the U.S. banking system

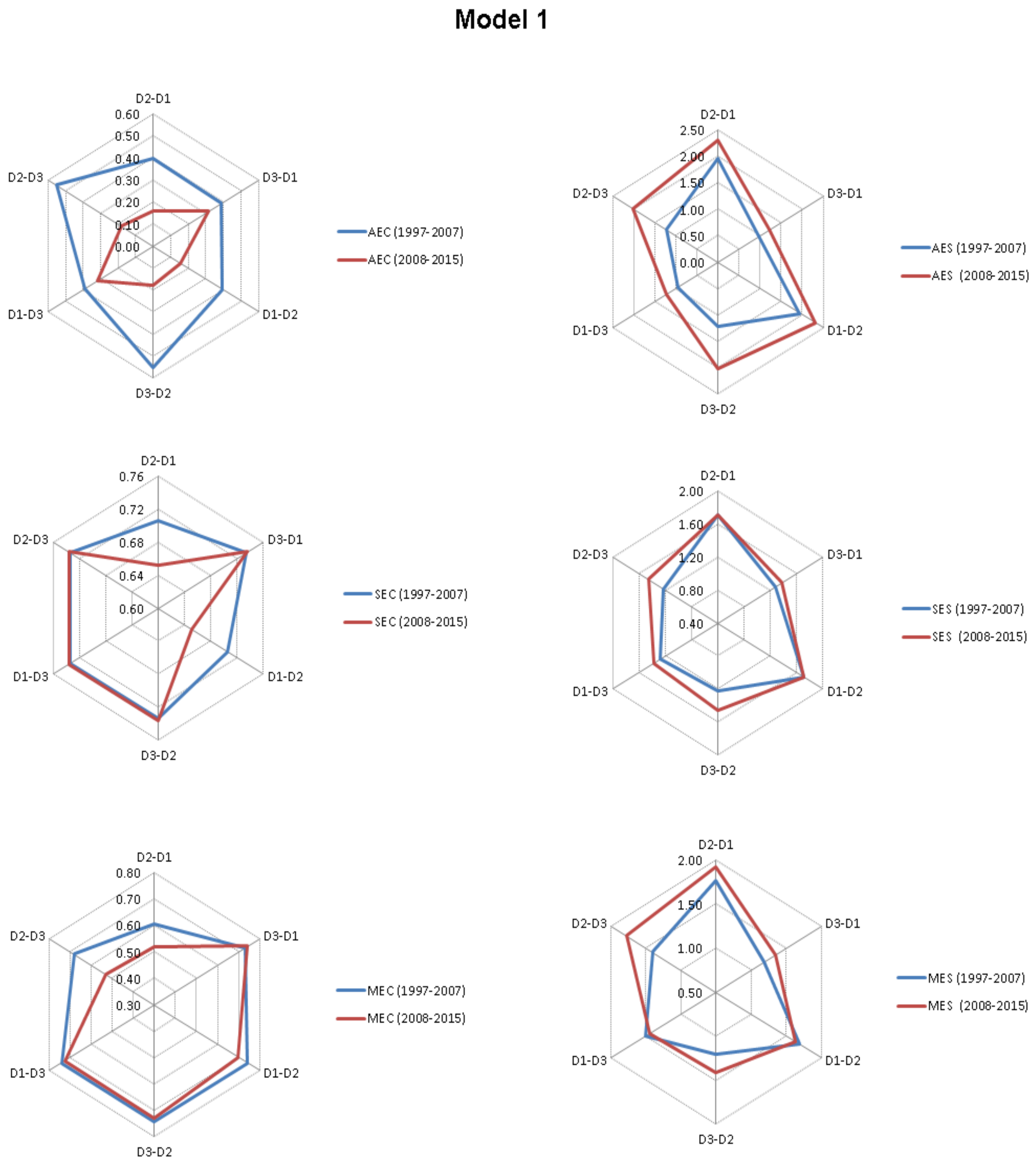

Figure 4: Radar diagrams of the elasticities of substitution and complementarity between the deposit types from model specification 1

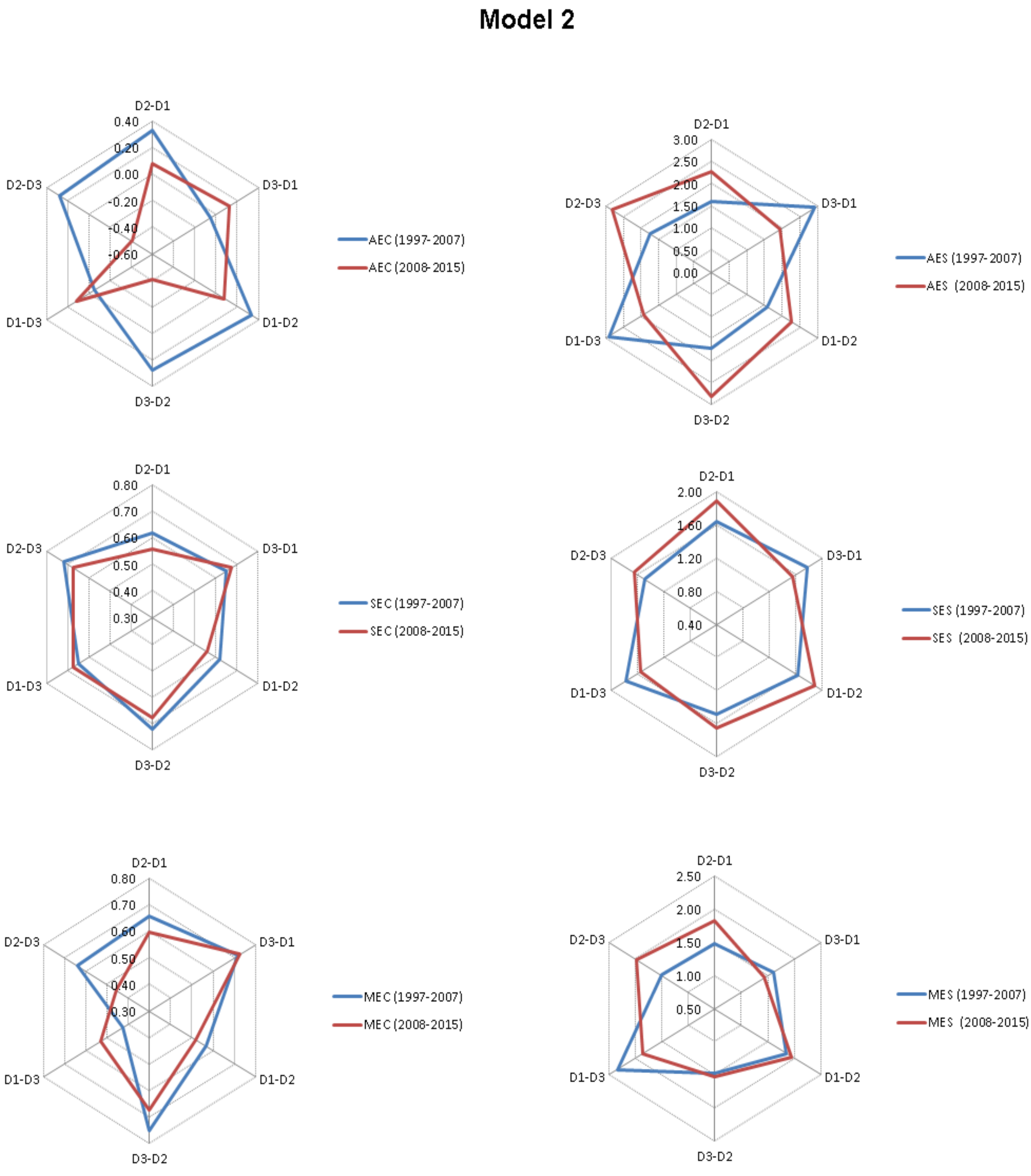

Figure 5: Radar diagrams of the elasticities of substitution and complementarity between the deposit types from model specification 2

Table 1: Variable descriptions and summary statistics

Variable description	Model notation	Mean 1992 – 2007	St. Dev. 1992 – 2007	Mean 2008 – 2015	St. Dev. 2008 – 2015
Included in all three model specifications					
Labor: Full-time equivalent total employees	x_1	203	2,556	331	5,249
Premises and fixed assets (000s 2005 U.S. $)	x_2	10,554	122,783	16,968	212,453
Loans: Net loans and leases (in 000s 2005 U.S. $)	y_1	502,322	7,289,277	998,921	16,087,245
Total securities (in 000s 2005 U.S. $)	y_2	159,232	2,085,237	365,115	6,684,075
Total non-interest income (in 000s 2005 U.S. $)	y_3	17,196	313,789	29,712	661,950
Return on assets	$RoA = z_1$	1.10	0.77	0.69	1.10
Bank asset market share: Each bank's total assets as a share of industry assets	$MS = z_2$	0.0001	0.0018	0.0002	0.0034
Equity ratio: Total equity capital divided by total assets	$ER = z_3$	0.10	0.03	0.11	0.03
Indicator equal to 1 (0) if the bank is (not) among the 100 largest banks measured by total assets in the country in each year	$Top = z_4$	0.01	0.11	0.02	0.13
Security share: Securities (y_2) as a share of of total assets	$SEC = z_5$	0.28	0.15	0.23	0.15
Hirschman-Herfindahl Index (HHI) of each bank's asset portfolio across real estate loans, farm loans, commercial and industrial loans, loans to individuals and other loans as ratios of total loans	$Scope = z_6$	0.49	0.16	0.58	0.17
Loan loss allowance as a share of loans (y_1)	$LLA = z_7$	0.02	0.01	0.02	0.01
Number of years the institution has been established	$Age = z_8$	70	39	80	41
Number of domestic U.S. branches	$Branches = z_9$	9	72	16	156
Included in model specification 1 only					
Transaction accounts of individuals, partnerships and corporations (in 000s 2005 U.S. $)	x_3	95,532	949,775	163,859	2,857,452
Non-transaction accounts of individuals, partnerships and corporations (in 000s 2005 U.S. $)	x_4	374,438	5,014,431	926,075	15,517,824
Other transaction and other non-transaction accounts (in 000s 2005 U.S. $)	x_5	34,520	414,379	89,763	1,283,289
Included in model specification 2 only					
Total time deposits (in 000s 2005 U.S. $)	x_3	176,348	1,651,763	234,107	2,569,671
Total savings deposits (in 000s 2005 U.S. $)	x_4	249,791	3,856,166	794,160	14,578,740
Other deposits (in 000s 2005 U.S. $)	x_5	78,352	935,801	151,431	2,916,269
Included in model specification 3 only					
Non-interest-bearing deposits (in 000s 2005 U.S. $)	x_3	111,246	1,835,003	319,130	6,598,007
Interest-bearing deposits (in 000s 2005 U.S. $)	x_4	393,245	4,492,803	860,568	13,013,998

Table 2: Model specification 1 estimation results for the 1992-2007 and 2008-2015 input distance functions

Before the crisis $(1992-2007)$				Crisis and beyond $(2008-2015)$			
y_1	-0.430^{***}	y_3x_4	-0.007^{***}	y_1	-0.463^{***}	y_3x_4	0.000
y_2	-0.417^{***}	y_3x_5	0.001	y_2	-0.303^{***}	y_3x_5	-0.001
y_3	-0.073^{***}	t	0.005^{***}	y_3	-0.059^{***}	t	-0.007^{***}
x_2	0.006^{***}	t^2	0.000^{***}	x_2	0.016^{***}	t^2	0.003^{***}
x_3	0.183^{***}	y_1t	0.001^{***}	x_3	0.164^{***}	y_1t	0.001^{*}
x_4	0.498^{***}	y_2t	0.003^{***}	x_4	0.453^{***}	y_2t	0.000
x_5	0.065^{***}	y_3t	-0.001^{***}	x_5	0.070^{***}	y_3t	0.000
y_1^2	-0.067^{***}	x_2t	0.000	y_1^2	-0.054^{***}	x_2t	0.000
y_2^2	-0.038^{***}	x_3t	0.001^{***}	y_2^2	-0.025^{***}	x_3t	0.003^{***}
y_3^2	-0.014^{***}	x_4t	-0.003^{***}	y_3^2	-0.009^{***}	x_4t	-0.002^{***}
y_1y_2	0.096^{***}	x_5t	0.000^{*}	y_1y_2	0.062^{***}	x_5t	0.000
y_1y_3	0.032^{***}	RoA	0.010^{***}	y_1y_3	0.022^{***}	RoA	0.005^{***}
y_2y_3	-0.007^{***}	MS	-2.184^{***}	y_2y_3	-0.006^{***}	MS	2.440^{***}
x_2^2	0.000	ER	0.452^{***}	x_2^2	0.002^{***}	ER	0.684^{***}
x_3^2	0.027^{***}	Top	0.016^{***}	x_3^2	0.027^{***}	Top	0.003
x_4^2	0.048^{***}	SEC	0.799^{***}	x_4^2	0.044^{***}	SEC	0.523^{***}
x_5^2	0.015^{***}	$Scope$	0.034^{***}	x_5^2	0.015^{***}	$Scope$	-0.013^{*}
x_2x_3	-0.010^{***}	LLA	-1.617^{***}	x_2x_3	-0.003^{*}	LLA	-1.095^{***}
x_2x_4	0.007^{***}	Age	0.000	x_2x_4	0.006^{***}	Age	0.008^{***}
x_2x_5	-0.001^{**}	$Branches$	-0.174^{***}	x_2x_5	-0.002	$Branches$	-0.252^{***}
x_3x_4	-0.055^{***}	$Intercept$	-0.249^{***}	x_3x_4	-0.063^{***}	$Intercept$	-0.170^{***}
x_3x_5	-0.007^{***}	*Random Effects Parameters*		x_3x_5	-0.008^{***}	*Random Effects Parameters*	
x_4x_5	-0.015^{***}	$sd(x_3)$	0.110^{***}	x_4x_5	-0.026^{***}	$sd(x_3)$	0.097^{***}
y_1x_2	-0.009^{***}	$sd(x_4)$	0.143^{***}	y_1x_2	-0.004^{***}	$sd(x_4)$	0.143^{***}
y_1x_3	-0.007^{***}	$sd(x_5)$	0.046^{***}	y_1x_3	-0.006^{***}	$sd(x_5)$	0.050^{***}
y_1x_4	0.018^{***}	$sd(Intercept)$	0.120^{***}	y_1x_4	0.009^{***}	$sd(Intercept)$	0.151^{***}
y_1x_5	0.003^{***}	$corr(x_3, x_4)$	-0.019	y_1x_5	0.004^{***}	$corr(x_3, x_4)$	0.014
y_2x_2	0.010^{***}	$corr(x_3, x_5)$	0.030	y_2x_2	0.003^{***}	$corr(x_3, x_5)$	-0.029
y_2x_3	-0.004^{***}	$corr(x_3, Intercept)$	0.045^{**}	y_2x_3	0.003^{**}	$corr(x_3, Intercept)$	0.015
y_2x_4	-0.017^{***}	$corr(x_4, x_5)$	-0.089^{***}	y_2x_4	-0.011^{***}	$corr(x_4, x_5)$	-0.065^{*}
y_2x_5	-0.009^{***}	$corr(x_4, Intercept)$	0.024	y_2x_5	-0.005^{***}	$corr(x_4, Intercept)$	0.055^{*}
y_3x_2	0.002^{***}	$corr(x_5, Intercept)$	0.078^{***}	y_3x_2	0.004^{***}	$corr(x_5, Intercept)$	0.114^{***}
y_3x_3	0.003^{***}			y_3x_3	-0.001		

*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

sd and corr denote standard deviation and correlation, respectively.

Table 3: Model specification 2 estimation results for the 1992-2007 and 2008-2015 input distance functions

Before the crisis (1992 – 2007)				Crisis and beyond (2008 – 2015)			
y_1	-0.435^{***}	y_3x_4	0.002	y_1	-0.488^{***}	y_3x_4	-0.004^{***}
y_2	-0.423^{***}	y_3x_5	-0.004^{***}	y_2	-0.286^{***}	y_3x_5	0.001
y_3	-0.072^{***}	t	0.005^{***}	y_3	-0.057^{***}	t	-0.005^{***}
x_2	0.005^{***}	t^2	0.000^{***}	x_2	0.017^{***}	t^2	0.003^{***}
x_3	0.369^{***}	y_1t	0.000	x_3	0.300^{***}	y_1t	-0.001^{***}
x_4	0.275^{***}	y_2t	0.003^{***}	x_4	0.284^{***}	y_2t	-0.001^{***}
x_5	0.109^{***}	y_3t	-0.001^{***}	x_5	0.106^{***}	y_3t	0.000
y_1^2	-0.068^{***}	x_2t	0.000^{***}	y_1^2	-0.051^{***}	x_2t	0.000
y_2^2	-0.038^{***}	x_3t	-0.001^{***}	y_2^2	-0.023^{***}	x_3t	-0.003^{***}
y_3^2	-0.013^{***}	x_4t	-0.001^{***}	y_3^2	-0.009^{***}	x_4t	0.004^{***}
y_1y_2	0.099^{***}	x_5t	0.000	y_1y_2	0.053^{***}	x_5t	0.003^{***}
y_1y_3	0.030^{***}	RoA	0.014^{***}	y_1y_3	0.023^{***}	RoA	0.005^{***}
y_2y_3	-0.008^{***}	MS	-5.911^{***}	y_2y_3	-0.005^{***}	MS	1.849^{**}
x_2^2	0.001^{*}	ER	0.449^{***}	x_2^2	0.002^{***}	ER	0.724^{***}
x_3^2	0.069^{***}	Top	0.014^{**}	x_3^2	0.062^{***}	Top	-0.003
x_4^2	0.043^{***}	SEC	0.809^{***}	x_4^2	0.041^{***}	SEC	0.423^{***}
x_5^2	0.019^{***}	$Scope$	0.037^{***}	x_5^2	0.019^{***}	$Scope$	-0.020^{***}
x_2x_3	0.000	LLA	-1.688^{***}	x_2x_3	-0.005^{**}	LLA	-1.249^{***}
x_2x_4	-0.001	Age	0.002^{**}	x_2x_4	0.002	Age	0.009^{***}
x_2x_5	0.003^{***}	$Branches$	-0.166^{***}	x_2x_5	-0.002	$Branches$	-0.246^{***}
x_3x_4	-0.068^{***}	$Intercept$	-0.254^{***}	x_3x_4	-0.078^{***}	$Intercept$	-0.148^{***}
x_3x_5	-0.042^{***}	*Random Effects Parameters*		x_3x_5	-0.028^{***}	*Random Effects Parameters*	
x_4x_5	-0.022^{***}	$sd(x_3)$	0.114^{***}	x_4x_5	-0.042^{***}	$sd(x_3)$	0.111^{***}
y_1x_2	-0.008^{***}	$sd(x_4)$	0.117^{***}	y_1x_2	-0.004^{***}	$sd(x_4)$	0.105^{***}
y_1x_3	0.001	$sd(x_5)$	0.091^{***}	y_1x_3	0.000	$sd(x_5)$	0.074^{***}
y_1x_4	0.019^{***}	$sd(Intercept)$	0.116^{***}	y_1x_4	0.019^{***}	$sd(Intercept)$	0.144^{***}
y_1x_5	0.002	$corr(x_3, x_4)$	-0.060^{***}	y_1x_5	0.002	$corr(x_3, x_4)$	0.026
y_2x_2	0.011^{***}	$corr(x_3, x_5)$	-0.095^{***}	y_2x_2	0.003^{***}	$corr(x_3, x_5)$	0.114^{***}
y_2x_3	-0.020^{***}	$corr(x_3, Intercept)$	0.006	y_2x_3	-0.011	$corr(x_3, Intercept)$	0.027
y_2x_4	-0.018^{***}	$corr(x_4, x_5)$	-0.058^{**}	y_2x_4	0.000	$corr(x_4, x_5)$	0.144^{***}
y_2x_5	0.004^{***}	$corr(x_4, Intercept)$	0.003	y_2x_5	0.000	$corr(x_4, Intercept)$	0.080^{***}
y_3x_2	0.000	$corr(x_5, Intercept)$	0.138^{***}	y_3x_2	0.003	$corr(x_5, Intercept)$	0.152^{***}
y_3x_3	0.003^{*}			y_3x_3	-0.003		

*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.
sd and corr denote standard deviation and correlation, respectively.

Table 4: Model specification 3 estimation results for the 1992-2007 and 2008-2015 input distance functions

Before the crisis (1992 − 2007)				Crisis and beyond (2008 − 2015)			
y_1	-0.436^{***}	y_3x_4	0.003^{*}	y_1	-0.486^{***}	y_3x_4	-0.006^{***}
y_2	-0.418^{***}	t	0.005^{***}	y_2	-0.293^{***}	t	-0.007^{***}
y_3	-0.074^{***}	t^2	0.000^{***}	y_3	-0.061^{***}	t^2	0.003^{***}
x_2	0.005^{***}	y_1t	0.001^{***}	x_2	0.015^{***}	y_1t	0.000
x_3	0.114^{***}	y_2t	0.003^{***}	x_3	0.115^{***}	y_2t	0.000
x_4	0.639^{***}	y_3t	-0.001^{***}	x_4	0.576^{***}	y_3t	0.000
y_1^2	-0.068^{***}	x_2t	0.000^{**}	y_1^2	-0.055^{***}	x_2t	0.000
y_2^2	-0.038^{***}	x_3t	0.001^{***}	y_2^2	-0.024^{***}	x_3t	0.003^{***}
y_3^2	-0.014^{***}	x_4t	-0.004^{***}	y_3^2	-0.009^{***}	x_4t	-0.001
y_1y_2	0.101^{***}	RoA	0.014^{***}	y_1y_2	0.060^{***}	RoA	0.005^{***}
y_1y_3	0.032^{***}	MS	-5.011^{***}	y_1y_3	0.025^{***}	MS	2.944^{***}
y_2y_3	-0.010^{***}	ER	0.461^{***}	y_2y_3	-0.007^{***}	ER	0.694^{***}
x_2^2	0.000	Top	0.020^{***}	x_2^2	0.002^{***}	Top	0.009
x_3^2	0.015^{***}	SEC	0.775^{***}	x_3^2	0.023^{***}	SEC	0.428^{***}
x_4^2	0.065^{***}	$Scope$	0.038^{***}	x_4^2	0.036^{***}	$Scope$	-0.018^{**}
x_2x_3	-0.001	LLA	-1.669^{***}	x_2x_3	-0.003	LLA	-1.190^{***}
x_2x_4	0.003^{*}	Age	0.002	x_2x_4	0.000	Age	0.012^{***}
x_3x_4	-0.071^{***}	$Branches$	-0.171^{***}	x_3x_4	-0.082^{***}	$Branches$	-0.241^{***}
y_1x_2	-0.009^{***}	$Intercept$	-0.224^{***}	y_1x_2	-0.004^{***}	$Intercept$	-0.115^{***}
y_1x_3	0.002	*Random Effects Parameters*		y_1x_3	0.006^{***}	*Random Effects Parameters*	
y_1x_4	0.013^{***}	$sd(x_3)$	0.108^{***}	y_1x_4	0.024^{***}	$sd(x_3)$	0.097^{***}
y_2x_2	0.010^{***}	$sd(x_4)$	0.172^{***}	y_2x_2	0.003^{***}	$sd(x_4)$	0.174^{***}
y_2x_3	0.002^{***}	$sd(Intercept)$	0.125^{***}	y_2x_3	0.003^{***}	$sd(Intercept)$	0.145^{***}
y_2x_4	-0.040^{***}	$corr(x_3, x_4)$	-0.175^{***}	y_2x_4	-0.028^{***}	$corr(x_3, x_4)$	-0.093^{***}
y_3x_2	0.002^{*}	$corr(x_3, Intercept)$	0.084^{***}	y_3x_2	0.003^{***}	$corr(x_3, Intercept)$	0.077^{***}
y_3x_3	-0.001	$corr(x_4, Intercept)$	-0.002	y_3x_3	0.000	$corr(x_4, Intercept)$	0.035
y_3x_4	0.003^{*}			y_3x_4	-0.006^{***}		

*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

sd and corr denote standard deviation and correlation, respectively.

Table 5: Elasticities of substitution and complementarity between deposit types from model specification 1 of the input distance function

	Model 1 (1992 – 2007)							Model 1 (2008 – 2015)					
	AEC	SEC	MEC	AES	SES	MES		AEC	SEC	MEC	AES	SES	MES
D2-D1	0.40***	0.71***	0.60***	1.94	1.71	1.76	D2-D1	0.16***	0.65***	0.52***	2.31	1.70	1.92
D3-D1	0.39***	0.73***	0.73***	0.96	1.27	1.19	D3-D1	0.32**	0.74***	0.74***	1.23	1.38	1.35
D1-D2	0.40***	0.71***	0.74***	1.94	1.71	1.69	D1-D2	0.16***	0.65***	0.70***	2.31	1.70	1.63
D3-D2	0.55***	0.73***	0.74***	1.23	1.23	1.21	D3-D2	0.18**	0.74***	0.73***	2.01	1.46	1.41
D1-D3	0.39***	0.73***	0.74***	0.96	1.27	1.51	D1-D3	0.32**	0.74***	0.73***	1.23	1.38	1.45
D2-D3	0.55***	0.73***	0.68***	1.23	1.23	1.41	D2-D3	0.18**	0.74***	0.53***	2.01	1.46	1.78

For asymmetric elasticities of substitution and complementarity the price or quantity of the first input in a pair changes.
D1 denotes transaction accounts of individuals, partnerships and corporations; D2 denotes non-transaction accounts of individuals, partnerships and corporations; D3 denotes other transaction and other non-transaction accounts.
Standard errors for the elasticities of complementarity are calculated using the delta method.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 6: Elasticities of substitution and complementarity between deposit types from model specification 2 of the input distance function

	Model 2 (1992 – 2007)							Model 2 (2008 – 2015)					
	AEC	SEC	MEC	AES	SES	MES		AEC	SEC	MEC	AES	SES	MES
D2-D1	0.33***	0.62***	0.66***	1.59	1.63	1.47	D2-D1	0.08*	0.56***	0.60***	2.27	1.89	1.83
D3-D1	−0.05	0.65***	0.71***	2.91	1.77	1.60	D3-D1	0.12	0.68***	0.73***	1.93	1.55	1.44
D1-D2	0.33***	0.62***	0.57***	1.59	1.63	1.85	D1-D2	0.08*	0.56***	0.52***	2.27	1.89	1.95
D3-D2	0.28***	0.72***	0.75***	1.73	1.49	1.48	D3-D2	−0.41***	0.68***	0.67***	2.80	1.65	1.53
D1-D3	−0.05	0.65***	0.43***	2.91	1.77	2.34	D1-D3	0.12	0.68***	0.53***	1.93	1.55	1.85
D2-D3	0.28***	0.72***	0.64***	1.73	1.49	1.51	D2-D3	−0.41***	0.68***	0.46***	2.80	1.65	1.98

For asymmetric elasticities of substitution and complementarity the price or quantity of the first input in a pair changes.
D1 denotes total time deposits; D2 denotes total savings deposits; D3 denotes other deposits.
Standard errors for the elasticities of complementarity are calculated using the delta method.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 7: Elasticities of substitution and complementarity between deposit types from model specification 3 of the input distance function

	Model 3 (1992 – 2007)							Model 3 (2008 – 2015)					
	AEC	SEC	MEC	AES	SES	MES		AEC	SEC	MEC	AES	SES	MES
D2-D1	0.02	0.68***	0.27***	2.87	1.89	2.64	D2-D1	−0.24***	0.59***	0.23***	3.23	1.96	2.65
D1-D2	0.02	0.68***	0.76***	2.87	1.89	1.75	D1-D2	−0.24***	0.59***	0.66***	3.23	1.96	1.82

For asymmetric elasticities of substitution and complementarity the price or quantity of the first input in a pair changes.
D1 denotes non-interest bearing deposits; D2 denotes interest bearing deposits.
Standard errors for the elasticities of complementarity are calculated using the delta method.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 8: Z-scores for tests of the 2008-2015 elasticities of complementarity against the corresponding 1992-2007 elasticity

	Model 1				Model 2				Model 3		
	AEC	SEC	MEC		AEC	SEC	MEC		AEC	SEC	MEC
D2-D1	5.48***	1.66*	2.54**	D2-D1	6.29***	2.45**	2.00*	D2-D1	4.18***	1.59	0.93
D3-D1	0.56	−0.05	−0.16	D3-D1	−2.10*	−0.49	−0.21				
D1-D2	5.48***	1.66*	1.20	D1-D2	6.29***	2.45**	1.81*	D1-D2	4.18***	1.59	1.47
D3-D2	5.66***	0.56	0.18	D3-D2	6.83***	1.85*	1.19				
D1-D3	0.56	−0.05	0.27	D1-D3	−2.10*	−0.49	−2.10*				
D2-D3	5.66***	0.56	3.22***	D2-D3	6.83***	1.85*	3.21***				

Model 1: D1 denotes transaction accounts of individuals, partnerships and corporations; D2 denotes non-transaction accounts of individuals, partnerships and corporations; D3 denotes other transaction and other non-transaction accounts.
Model 2: D1 denotes total time deposits; D2 denotes total savings deposits; D3 denotes other deposits.
Model 3: D1 denotes non-interest bearing deposits; D2 denotes interest bearing deposits.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels, respectively.