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Adapting to Changing Prices Before and After the Crisis: The Case of US Commercial Banks

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For banks, cost management has gained importance in the current environment of low interest rates. In this environment, banks' revenues from interest are under pressure, leading to renewed interest in the substitutability of banks' input factors. Substitution elasticities typically depend on two factors: cost technology and economic conditions (relative input prices or cost shares). Technological shifts and policy changes are therefore expected to affect firms' elasticities of substitution. This study estimates U.S. commercial banks' substitution elasticities during the 2000 – 2013 period. It analyzes the total effects of the technological shifts and policy changes on banks' substitution elasticities during that period. An endogenous-break test divides the sample into a pre-crisis period (2000 – 2008) and a crisis period (2009 – 2013). During the pre-crisis period, banks' inputs are inelastic substitutes. After the onset of the crisis, especially the long-run substitutability of most input factors decreases to even lower levels due to changes in both cost technology and economic conditions. At the same time, banks' response to input price changes becomes more sluggish. The results indicate that the availability of substitutes is substantially worse during the (post-) crisis period, which limits banks' possibilities for cost management.

Keywords

financial crisis, substitution elasticities, US commercial banks

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G21, D24, C30

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Adapting to Changing Prices Before and After the Crisis: The Case of U.S. Commercial Banks

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Abstract

For banks, cost management has gained importance in the current environment of low interest rates. In this environment, banks' revenues from interest are under pressure, leading to renewed interest in the substitutability of banks' input factors. Substitution elasticities typically depend on two factors: cost technology and economic conditions (relative input prices or cost shares). Technological shifts and policy changes are therefore expected to affect firms' elasticities of substitution. This study estimates U.S. commercial banks' substitution elasticities during the 2000 – 2013 period. It analyzes the total effects of the technological shifts and policy changes on banks' substitution elasticities during that period. An endogenous-break test divides the sample into a pre-crisis period (2000 – 2008) and a crisis period (2009 – 2013). During the pre-crisis period, banks' inputs are inelastic substitutes. After the onset of the crisis, especially the long-run substitutability of most input factors decreases to even lower levels due to changes in both cost technology and economic conditions. At the same time, banks' response to input price changes becomes more sluggish. The results indicate that the availability of substitutes is substantially worse during the (post-) crisis period, which limits banks' possibilities for cost management.

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1. Introduction

Substitution elasticities quantify the extent to which the demand for inputs responds to changes in input prices. They are considered particularly relevant from the perspective of cost management. For example, when the input price of one or more inputs increases, firms can mitigate higher total costs by replacing the inputs by substitutes whose prices have increased to a lesser extent. Firm's substitution elasticities typically depend on two factors: cost technology and economic conditions such as relative input prices or cost shares (Frondel and Schmidt, 2006). The same cost technology might yield different substitution elasticities under different economic conditions.

Technological shifts and policy changes are expected to affect firms' elasticities of substitution to the extent that they affect firms' cost technology and economic conditions. The literature has indeed observed changes in firms' substitution elasticities in response to such changes. For example, Noulas et al. (1990) documents a higher degree of substitutability among bank input factors after deregulation. Also in other industries, policy changes have been associated with changes in substitution elasticities; see e.g. Considine (1989b) and Steinbuks (2012) who analyze the changes in interfuel substitutability.

For banks, cost management has gained importance in the current environment of low interest rates. In this environment, banks' revenues from interest are under pressure, resulting in renewed interest in the substitutability of banks' input factors. This study analyzes U.S. commercial banks' substitution elasticities during the 2000 – 2013 period, thereby covering years that were characterized by regulatory, monetary and technological change. In particular, the global financial crisis started with the fall of Lehman Brothers in September 2008 and was preceded by the U.S. credit crisis of 2007 – 2008 (Guillén, 2009). Changes in monetary policy (such as the Federal Reserve's quantitative easing) and enhanced regulation on banks (e.g., the Dodd-Frank Act) are likely to have affected banks' cost technology and economic environment. Much lower interest rates and lower growth have subsequently prevailed. Another important development was a technological shift concurrent to the crisis: the ongoing adoption of online banking technology in the form of transactional web sites and mobile banking apps. The literature has associated the adoption of online banking technology with changes in banks' input mix and input prices (DeYoung et al., 2007). The overall effect of the aforementioned policy and technological change on U.S. commercial banks' substitution elasticities is theoretically not a priori clear. This is an empirical question that will be addressed in this study, though we confine our analysis to exploring the actual changes in elasticities rather than attempting to identify causal factors.

The standard approach to estimate substitution elasticities is based on static demand systems, such as the ones implied by a long-run cost function or a short-run restricted variable cost function. The latter cost function implies a static partial equilibrium with respect to the variable inputs, conditional upon the level of one or more quasi-fixed inputs (Hughes and Mester, 1993; Hunter and Timme, 1995; Mester, 1996). In this case only short-run elasticities can be derived. Long-run cost functions, by contrast, assume that all inputs are completely variable and observed at their long-run equilibrium levels (e.g. Pindyck and Rotemberg, 1983; Hunter and Timme, 1995). Yet it is well-known that input factors such as labor and capital are not fully flexible in the short run due to the existence of adjustment costs, technological constraints and institutional rigidities, among others. Static demand systems are not only misspecified, but also overlook dynamics that are interesting in themselves. The dynamics provide information about the speed at which input price changes are incorporated in the demand for inputs (known as the *lag time*) and shed light on the availability of substitutes in the short run and long run.

To analyze the U.S. commercial banks' substitution elasticities, this study estimates a Dynamic Logit Demand (DLD) system (Considine and Mount, 1984; Considine, 1989a; Shui et al., 1993; Jones, 1995, 1996; Brännlund and Lundgren, 2004; Steinbuks, 2012). The DLD system provides insight in the short-run (SR) and long-run (LR) effects of changes in input prices on the demand for these inputs, as well as the lag time. In contrast to the logit model of discrete choice, the logit demand system does not assume independence of irrelevant alternatives (Considine, 1989b, 1990). Consequently, the estimated elasticities are fully unrestricted. Several empirical studies have confirmed that the DLD system naturally satisfies the properties of a proper demand system and that it is more suitable for estimating SR and LR elasticities than the dynamic translog demand system (Jones, 1995; Urga and Walters, 2003). We estimate a DLD system to obtain SR and LR substitution elasticities, as well as median lag times. To our best knowledge, we are the first to analyze the dynamics of banks' response to changes in input prices.

We run an endogenous break test (Andrews, 1993) to allow for structural change during the 2000 – 2013 period. The sup-Wald test identifies a pre-crisis period (2000 – 2008) and a (post-) crisis period (2009 – 2013). We estimate DLD systems and the associated substitution elasticities for both periods. During the first period, banks' median lag time is about 4.3 years and most input factors are inelastic substitutes, both in the SR and the LR. Banks' median lag time increases by more than 50% after the onset of the crisis (to 6.5 years). The SR and LR substitutability of virtually all input factors is significantly lower during the (post-) crisis period, due to changes in both cost technology and economic conditions. The results are consistent across banks of different sizes. Hence, the overall effect of the aforementioned policy and technological change on banks' substitution elasticities is mostly negative, leaving little room for cost management on the basis of input factor substitutability.

The finding of a statistically distinct breakpoint concurrent with the onset of the crisis strongly suggests that it was the crisis itself, rather than a coincident flow of confounding factors, that drove the observed decrease in substitution elasticities. The dramatic policy responses to the crisis – in both regulatory and monetary policy – seem likely candidates to underlie the elasticity changes. This reasoning is consistent with the findings of Noulas et al. (1990) that deregulation was associated with subsequently higher degrees of substitutability among bank input factors.

The setup of the remainder of this study is as follows. Section 2 reviews some relevant literature and recent developments regarding the substitutability of banks' input factors. The econometric methodology is discussed in Sections 3 and 4. Section 5 provides a description of the data on U.S. commercial banks, while Section 6 provides estimates of the DLD system and the associated estimatates of SR and LR substitution elasticities. Several robustness checks are performed in Section 7. Finally, Section 8 concludes. An online appendix with supplementary material is provided.

2. Background

According to the intermediation model of banking, banks use labor and physical capital to attract deposits (Klein, 1971; Monti, 1972; Sealey and Lindley, 1977). Deposits are used to fund loans and other earning assets. The production function underlying the intermediation model typically needs a dollar of deposits to generate a dollar of loans and other earning assets, net of reserve requirements. Empirical banking studies typically assume that banks operate according to the intermediation model of banking and assume a production technology consisting of, for instance, four inputs (purchased funds, core deposits, labor services, and physical capital) and five outputs (consumer loans, real estate loans, business and other loans, securities and off-balance sheet items); see e.g. Wheelock and Wilson (2012).

2.1. Substitutability of banks' input factors

The non-financial inputs physical capital and labor could be substitutes for each other because investments in technology (in the form of ATMs, computers, automatic credit scoring, online banking services and other technology) could allow fewer tellers and loan officers to serve the same number of bank customers. There is also another reason why labor and physical capital may act as substitutes for each other. A bank that relies more on off-balance-sheet business would assign relatively more staff to managing such activities rather than to traditional retail banking activities that rely on brick-and-mortar offices. The latter mechanism also suggests a reason why labor could be a substitute for core deposits.[1]

Given the nature of banks' production function, banks' financial and non-financial inputs are expected to be at best weak substitutes. For example, labor and physical capital may each be weak substitutes for purchased funds because a heavier reliance on purchased funds could allow a bank to generate the same amount of earning assets with a smaller amount of core deposits, thus economizing on branch offices, ATMs, and bank tellers needed to attract and retain core deposits. The financial and non-financial inputs can also be complements though (e.g. Wu et al., 2012). For example, more branch offices (a major component of physical capital) might be needed to attract more core deposits. Similarly, more deposits could require more loan officers to allocate the funds efficiently.

It is obvious that the financial inputs (core deposits and purchased funds) can act as substitutes for each other, but we might observe differences between small and large banks. As observed by Noulas et al. (1990), large banks in the U.S. typically operate according to a different business model than small banks. In particular, small banks tend to have less access to national money market funding (purchased funds) and thus are more constrained by their local market conditions. In addition, small banks have less opportunity to diversify than large banks, which can affect some of their input and production decisions. This might also affect the substitutability of the other input factors. More generally, the theoretical literature has argued that small and large firms are likely to differ in terms of production technology (Dupuy and De Grip, 2006). Several empirical studies have indeed revealed significant differences in

[1] A bank's use of outsourcing might also affect both its input mix and the degree of substitutability across inputs. Regulatory and practitioner sources report that some banks outsource various core and non-core business functions, potentially including IT, compliance, business acquisition, loan processing, account servicing, data processing, risk analysis, customer service, marketing, HR functions, procurement, training, collections, foreclosure, check processing, clearance and settlement services, fraud mitigation and detection, portfolio analytics, and credit evaluation, verification, and approval.

substitution elasticities between large and small firms in various industries (e.g., Noulas et al., 1990; Lever, 1996; Dhawan, 2001). However, for banks this argument could be less relevant, since all banks face fundamentally the same production technology for traditional core banking activities (i.e., taking deposits and making loans). Although the largest banks heavily rely on trading and off-balance-sheet activities, it is a priori unclear whether this will be reflected in the empirical results given that the U.S. banking market is dominated by smaller banks with a more traditional focus.

Various studies have analyzed banks' and thrifts' substitution elasticities (e.g. Humphrey, 1981; Obben, 1993; Hancock, 1986; Noulas et al., 1990; Pantalone and Platt, 1994; Hunter and Timme, 1995; Stiroh, 1999; Wu et al., 2012). More recently, substitution elasticities have also been analyzed for microfinance institutions (Hartarska et al., 2013). These studies confirm that typical input factors such as labor, physical capital, purchased funds and core deposits tend to be inelastic substitutes.

2.2. Policy changes and technological shifts after the onset of the crisis

This subsection discusses several developments that may have affected U.S. banks' substitution elasticities during the 2000 – 2013 period and especially after the onset of the crisis.

2.2.1. Changes in monetary policy

During the pre-crisis years, commercial banks' aggregate federal funds sold rose steadily from $ 280 billion in 2000 to $ 443 billion in 2005, while federal funds purchased rose from $ 475 billion to nearly $ 668 billion. Total borrowed funds (considered a substitute for core deposits) likewise grew, along with total deposits and total assets, as shown in Table 1. Following the onset of the crisis, the Federal Reserve's subsequent quantitative easing sharply altered banks' mix of inputs and outputs. Federal funds sold declined from $ 688 billion in 2008 to less than $ 402 billion the following year – a 41% decline – while federal funds purchased fell from $ 804 billion to $ 551 billion over the same period; see Table 1. This new pattern has persisted in subsequent years, with federal funds sold totaling $ 356 billion and federal funds purchased totaling just $ 294 billion at year-end 2014, despite continued general growth of total deposits and total bank assets. Borrowed funds exhibited a similar decline. This sharp reduction in federal funds volume was driven in large part by the payment of interest on bank reserves by the Federal Reserve beginning in late 2008 (Ihrig et al., 2015); for the first time in U.S. history, banks could earn a higher yield on reserves compared to lending in the federal funds market. Following this change, aggregate reserves held by banks on the Fed's balance sheet rose dramatically from $ 14 billion in 2007 to $ 2.6 trillion in late 2014 (Ihrig et al., 2015, p. 185). These changes are expected to have altered banks' cost technology, thus affecting both the elasticities of substitution among inputs and the lag time, although the directions of such changes are ambiguous on purely theoretical grounds.

The onset of the crisis also affected banks' economic conditions. The Fed's quantitative easing policy resulted in a substantial drop in interest rates. For example, the yield on 10-year U.S. Treasury securities was roughly twice as high on average during 2000 – 2008 as it was during 2009 – 2013.[2] The effective Fed funds rate fell even more dramatically after 2008.[3] Consequently, the price of bank liabilities fell dramatically after 2008, causing a sharp decline in banks' cost share of interest expenses. Also this development is likely to have influenced banks' substitution elasticities.

2.2.2. *Regulatory changes*

In view of the scope and magnitude of the crisis, it is no surprise that the regulatory response was dramatic. The U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank hereafter) in 2010, two years after the onset of the crisis.[4] The delay was necessary to permit legislators to study the problem, identify possible solutions, and prepare their written response. The final Act occupied more than 2,300 pages of text and required U.S. regulatory agencies to draft some 400 new regulations to implement its various provisions. Its table of contents alone spans 15 pages.

A complete exposition of the Act's contents is beyond the scope of this section, but we highlight some aspects that illustrate the substantial change it imposed on the regulatory environment of U.S. banks. The Act created new agencies in the Consumer Financial Protection Bureau and the Financial Stability Oversight Council, so U.S. banks are now subject to scrutiny and regulatory intervention from additional sources.[5] It imposed more stringent and complex capital requirements on banks, and subjected the largest banks to extremely detailed financial

[2]Source: https://fred.stlouisfed.org/series/GS10.

[3]Source: https://fred.stlouisfed.org/series/EFFR.

[4]The Basel Committee on Banking Supervision similarly developed the Basel III regulatory framework, which was rolled out in multiple phases during 2011 – 2014. Since the final framework had not yet been announced nor fully implemented in the U.S. – by the end of our sample period, this section will focus exclusively on Dodd-Frank. Even so, Basel III further strengthens the regulatory motivation for our hypothesis that substitution elasticities likely changed and perhaps fell – after the onset of the crisis.

[5]The Act also incorporated numerous other changes to federal regulatory agencies.

"stress tests". It added new restrictions on banks' use of financial derivatives and asset securitization, including a component of mandatory risk retention in the latter. It required large banks to develop processes for orderly resolution in the event of extreme financial distress. It even included provisions related to corporate governance and financial compensation of banks senior management, as well as aspects of relationships between a bank and any external vendors it uses for outsourced services.

The aggregate cost of compliance with Dodd-Frank has been substantial. According to one official estimate, complying with just the first 224 associated rules costs the private sector more than 22 million staff hours each year.[6] Moreover, with the added regulatory complexity comes additional opportunity and incentive for strategic behavior by banks to evade the restrictions (Plosser, 2012; Hoenig, 2013).

Such dramatic changes in U.S. banking regulation would be expected to shift the cost structure of banks in various ways. Banks' input mix would likely shift as banks hired additional compliance staff and invested in technological solutions to automate some aspects of regulatory compliance.[7] The increased regulatory restrictions and scrutiny would likely reduce banks' flexibility in adjusting their input mixes in response to subsequent changes in input prices, thereby reducing input substitutability; this effect would be consistent with the findings of Noulas et al. (1990) that deregulation enhanced banks' input substitutability.

2.2.3. Technological changes

One of the most notable technological shifts concurrent with the crisis is the adoption of online banking technology in the form of transactional web sites and, more recently, mobile banking apps. This trend has been discussed as reducing banks' unit costs, enhancing consumers' convenience and choice, and providing a means of product differentiation (DeYoung et al., 2007; He, 2015). While intuition might suggest that online banking could permit banks to substitute away from physical branch offices, DeYoung et al. (2007) report contrary evidence that the online delivery channel has been used mainly as a complement to, rather than as a substitute for, branches of community banks.

DeYoung et al. (2007) also found that the adoption of transactional banking web sites was associated with other shifts in input mix and with systematic changes in input prices. In particu-

[6] See http://www.financialservices.house.gov/burdentracker.

[7] As an example, one of the authors personally knows of a small depository institution that increased its compliance staff from one to five in response to Dodd-Frank.

lar, online banking was correlated with increased use of brokered deposits (a subset of purchased funds) and with movements of deposits from checking accounts to money market deposit accounts, all of which imply an increased average funding cost for the adopting banks. Likewise, online banking was associated with higher average wage rates for bank employees.

While adoption of this new technology is endogenous, reflecting deliberate strategic choices by banks (He, 2015), those choices comprise rational responses to changes in available technology that are largely exogenous to any individual bank. Systematic input price changes, such as in wage rates, might reflect unobserved heterogeneity in the corresponding input that would be required to adopt and maintain the new technology at the bank level. All of these changes could potentially affect empirical estimates of input substitution elasticities and lag times, further motivating assessment of a potential shift over time in our sample.

2.3. Testable hypotheses

The empirical part of this study focuses on the overall effect of the aforementioned developments on commercial banks' substitution elasticities. We will thus test two following two hypotheses:

H1: There is a change in substitution elasticities after the onset of the crisis.

H2: The changes in hypothesis H1 depends on bank size.

We will also estimate banks' speed of adjustment or lag time, which reflects the time needed to find substitutes or complements. Regarding the impact of the crisis, we can think of at least two scenarios. The financial stress of the crisis could have made it more difficult for banks to find substitutes or complement, resulting in a longer lag time. Alternatively, financial stress could have made it more urgent for banks to adjust as promptly as possible to changes in input prices, resulting in a shorter lag time after the onset of the crisis. This leads to the hypothesis:

H3: There is a change in lag time after the onset of the crisis.

3. Dynamic logit demand system

The literature has proposed several dynamic demand systems. For example, we could estimate an equilibrium model consisting of a SR restricted variable cost function, variable input demand (or input-output) equations and shadow-value equations for quasi-fixed inputs (e.g., Morrison, 1988; Considine, 2000; Considine and Larson, 2012). However, this approach does not always yield economically plausible results (Friesen, 1992a). Alternatively, we could estimate a dynamic translog demand (DTD) system (Holly and Smith, 1989; Jones, 1995; Esho and

Sharpe, 1995; Allen and Urga, 1999; Urga, 1999; Urga and Walters, 2003). However, also this approach can turn out problematic (Considine, 1989a; Jones, 1995; Urga and Walters, 2003).

A well-defined input demand system is characterized by non-negative conditional input demand functions that are symmetric and zero-degree homogenous in input prices. Furthermore, the resulting LR elasticities should be larger in magnitude than SR elasticities according to the *Le Chatelier* principle (e.g., Considine, 2000; Rossana, 2007). The literature has shown that it is often easy to specify a dynamic logit demand (DLD) system that satisfies these requirements (Considine and Mount, 1984; Considine, 1989a; Shui et al., 1993; Jones, 1995, 1996; Brännlund and Lundgren, 2004; Steinbuks, 2012). This section discusses the DLD demand system and the estimation of U.S. banks' SR and LR substitution elasticities and lag times.

3.1. Specification and estimation

We assume a production technology consisting of four inputs and five outputs (Wheelock and Wilson, 2012). The choice of inputs and outputs is based on the intermediation model for banking (Klein, 1971; Monti, 1972). The four inputs we consider are purchased funds, core deposits, labor services, and physical capital. The corresponding input prices are the price of purchased funds of bank $i = 1, \ldots, N$ in year $t = 1, \ldots, T$ ($P_{1,it}$), the core deposit interest rate ($P_{2,it}$), the wage rate ($P_{3,it}$), and the price of physical capital ($P_{4,it}$). The demand for input k is denoted by by $Q_{k,it}$, for $k = 1, \ldots, 4$. Total costs (C_{it}) are defined as the sum of expenses on purchased funds, core deposits, personnel expenses, and expenses on physical capital. The five outputs that we look at are consumer loans (with output quantity $Y_{1,it}$), real estate loans ($Y_{2,it}$), business and other loans ($Y_{3,it}$), securities ($Y_{4,it}$) and off-balance sheet items ($Y_{5,it}$). The analysis below is easily adjusted to the case of less, more or different inputs and outputs.

The logit input demand system is based on the assumption of cost-minimizing behavior, such that $Q_{j,it} = \partial C_{it}/\partial P_{j,it}$ and $w_{j,it} = \partial \log(C_{it})/\partial \log(P_{j,it})$ according to Shephard's lemma. We emphasize that the assumption of cost minimization is also made in studies that estimate substitution elasticities using a (static or dynamic) translog cost function. The logit demand system is specified in terms of the j-th cost share $w_{j,it}$ for bank i at time t. Allowing for multiple outputs, non-neutral technical change and non-homotheticity, the cost shares in the static version of the model have the form

$$w_{j,it} = \exp(f_{j,it}) / \sum_{k=1}^{4} \exp(f_{k,it}), \tag{1}$$

where

$$f_{j,it} = \alpha_{ij} + \sum_{k=1}^{4} \beta_{jk} \log(P_{k,it}) + \sum_{\ell=1}^{5} \gamma_{j\ell} \log(Y_{\ell,it}) + \sum_{t} \delta_{jt} d_t + e_{j,it}. \tag{2}$$

Here α_{ij} is a bank-specific fixed effect, d_t a time dummy for year t, $\alpha_{ij}, \beta_{jk}, \gamma_{j\ell}$ and δ_{jt} (vectors of) coefficients, and $e_{j,it}$ a mean-zero error term that is uncorrelated with the explanatory variables.

From Equation (2), we observe that the cost shares are guaranteed to be non-negative thanks to their exponential form, which ensures that the input demand functions are non-negative. As shown by Considine (1990), zero-degree homogeneity in input prices symmetry of the conditional demand functions translate into the restrictions $\sum_{k=1}^{n} \beta_{jk} = 0$ for all j and $\bar{w}_j \beta_{jk} = \bar{w}_k \beta_{kj}$ (known as Slutsky symmetry), respectively. Here the $\bar{w}_j$s denotes the mean cost shares. The parameter constraints can easily be imposed in the estimation stage of the logit demand system. With the 4-th input arbitrarily chosen as the numéraire and zero-degree homogeneity and symmetry imposed, the reduced-form share-equation system reduces to

$$\begin{aligned} \log(w_{j,it}/w_{4,it}) \;&=\; (\alpha_{ij} - \alpha_{i4}) + \sum_{k=1}^{j-1} (\beta^*_{kj} - \beta^*_{k4}) \bar{w}_j \log(P_{k,it}/P_{4,it}) \\ &+\; \Big(- \sum_{k=1}^{j-1} \bar{w}_k \beta^*_{jk} - \sum_{k=j+1}^{4} \bar{w}_k \beta^*_{jk} - \bar{w}_j \beta^*_{j4} \Big) \log(P_{j,it}/P_{4,it}) \\ &+\; \sum_{k=j+1}^{3} (\beta^*_{jk} - \beta^*_{k4}) \bar{w}_k \log(P_{k,it}/P_{4,it}) \\ &+\; \sum_{\ell=1}^{5} (\gamma_{j\ell} - \gamma_{4\ell}) \log(Y_{\ell,it}) + \sum_{t=1}^{T} (\delta_{jt} - \delta_{4t}) d_t + e_{j,it} - e_{4,it} \qquad [j = 1, 2, 3], \end{aligned} \tag{3}$$

where $\beta^*_{jk} = \beta_{jk}/\bar{w}_k$ for $j \neq k$. The symmetry and linear homogeneity then translate into $\beta^*_{jk} = \beta^*_{kj}$ for $j \neq k$ and $\beta^*_{jj} = -\sum_{k \neq j} \beta^*_{jk} \bar{w}_k / \bar{w}_j$. The identifying restrictions that we impose are $\gamma_{4\ell} = \delta_{4t} = 0$. The substitution elasticities that we will obtain later are not influenced by these restrictions as noted by Considine (1990).

The extension to the *dynamic* logit demand (DLD) system is made by adding the lagged log input *quantity* of input factor j to Equation (2), which then changes into

$$f_{j,it} = \alpha_{ij} + \sum_{k=1}^{4} \beta_{jk} \log(P_{k,it}) + \sum_{\ell=1}^{5} \gamma_{j\ell} \log(Y_{\ell,it}) + \sum_{t} \delta_{jt} d_t + \sum_{p=1}^{4} \lambda_{jp} \log(Q_{p,it-1}) + e_{j,it}. \tag{4}$$

To achieve identification, each row of the matrix of adjustment coefficients (λ_{jp}) has to sum to the same constant (Moschini and Moro, 1994). If we choose this constant to be zero, we can simply add the lagged values of $\log(Q_{p,it}/Q_{4,it-1})$ for $p = 1, 2, 3$ as explanatory variable to each share equation in (3). The literature has focused on a simplified version of Equation (4) by imposing $\lambda_{jp} = 0$ for $p \neq j$ and $\lambda_{jj} = \lambda$, such that all share equation have a common adjustment coefficient. This is also the model that will be selected by a formal specification search in our empirical example. We will therefore focus on the resulting version of the DLD model in the sequel:

$$
\begin{aligned}
\log(w_{j,it}/w_{4,it}) &= (\alpha_{ji} - \alpha_{4i}) + \sum_{k=1}^{j-1}(\beta^*_{kj} - \beta^*_{k4})\bar{w}_j \log(P_{k,it}/P_{4,it}) \\
&+ \Big(-\sum_{k=1}^{j-1} \bar{w}_k\beta^*_{jk} - \sum_{k=j+1}^{4} \bar{w}_k\beta^*_{jk} - \bar{w}_j\beta^*_{j4}\Big)\log(P_{j,it}/P_{4,it}) \\
&+ \sum_{k=j+1}^{3}(\beta^*_{jk} - \beta^*_{k4})\bar{w}_k \log(P_{k,it}/P_{4,it}) + \sum_{\ell=1}^{5}(\gamma_{j\ell} - \gamma_{4\ell})\log(Y_{\ell,it}) \\
&+ \lambda \log(Q_{j,it}/Q_{4,it-1}) + \sum_{t=1}^{T}(\delta_{jt} - \delta_{4t})d_t + e_{j,it} - e_{4,it},
\end{aligned} \tag{5}
$$

$\beta^*_{jk} = \beta_{jk}/\bar{w}_k$ for $j \neq k$. In Considine and Mount (1984) it is shown that this DLD model is a reduced-form equation based on a structural dynamic Treadway-type of model with adjustment costs, providing a formal theoretical motivation of the dynamic extension (Treadway, 1971, 1974).

The literature has estimated the logit demand system by means of Zellner's iterative SUR-GLS, because of its invariance with respect to the choice of the normalizing input (Considine and Mount, 1985).[8] We will come back to the estimation method in Section 4.1.

3.2. Substitution elasticities

We follow Frondel (2004, 2011) and focus on the own-price and cross-price elasticities of demand.[9] On the basis of (5), the SR elasticities take the form

$$
E^{SR}_{jj} = \frac{\partial \log(Q_{j,it})}{\partial \log(P_{j,it})} = \bar{w}_j\beta^*_{jj} + \bar{w}_j - 1, \quad E^{SR}_{jk} = \frac{\partial \log(Q_{j,it})}{\partial \log(P_{k,it})} = \bar{w}_k\beta^*_{jk} + \bar{w}_k \qquad [j \neq k], \tag{6}
$$

[8]An explanation for the invariance is that, under normality, iterative SUR-GLS estimation of logit demand systems is equivalent to maximum likelihood (ML) estimation; see Considine and Mount (1985). Maximum likelihood, in turn, is known for its invariance since Barten (1969). He showed that ML estimates of the parameters in singular n-equation systems with i.i.d. normally distributed errors can be derived from ML estimation of $n - 1$ equations and that the resulting ML estimates are invariant to the omitted equation.

[9]This choice is motivated in more detail in the appendix with supplementary material.

where $\bar{w}_j$ denotes the mean j-th cost share (Considine and Mount, 1984; Anderson and Thursby, 1986). The resulting price elasticities for each input sum to zero and satisfy Slutsky-symmetry; i.e., $\sum_{k=1}^{4} E_{jk}^{SR} = 0$ and $(E_{jk}^{SR} + \bar{w}_k)\bar{w}_j = (E_{kj}^{SR} + \bar{w}_j)\bar{w}_k$.

Frondel (2011) refers to the cross-price elasticity as a 'one-price-one-factor' elasticity of substitution, which provides a measure of absolute substitutability. We will later repeat the entire analysis using Morishima elasticities (known as 'one-price-two-factor' elasticities of substitution), which measure relative substitutability of input factors. We do not report the Allen-Uzawa partial elasticities of substitution. Blackorby and Russell (1989) show that, with more than two inputs, the latter elasticities do not measure substitutability in the sense of Hicks (1932). Moreover, as a qualitative measure they provide no additional information in addition to the cross-price elasticities of demand. Stiroh (1999) confirms that the Allen-Uzawa elasticities can be misleading about the magnitude of substitution effects in empirical applications.

As pointed out by Considine and Mount (1984), the LR elasticities in the DLD model with common adjustment coefficient λ can be expressed in terms of the SR elasticities and λ as

$$E_{jk}^{LR} = E_{jk}^{SR}/(1 - \lambda). \tag{7}$$

It is readily seen that the LR price elasticities for each input sum to zero and satisfy-Slutsky symmetry whenever the SR elasticities do so. Furthermore, the SR and LR elasticities satisfy the *Le Chatelier* principle for $\lambda > 0$.[10]

4. Estimation strategy

This section elaborates on the estimation method and the test for structural change.

4.1. Estimation of model coefficients and confidence intervals

Because the within variation in the explanatory variables (input prices, lagged cost shares and output quantities) is small in comparison to the between variation, we opt for pooled estimation. This estimation strategy makes use of both the within and the between variation in the data. Yet to allow for possible differences in cost technology between independent banks and banks that are part of a bank-holding company, we follow Wheelock and Wilson (2012) and

[10]We notice that the DLD system is only informative about substitution elasticities and not about economies of scale or scope (Considine, 1990), which would require the estimation of a total cost function. Consequently, the DLD system and its associated substitution elasticities are not prone to misspecification with respect to the way total costs depend on output.

include in each cost-share equation a binary variable indicating whether bank i is part of a bank holding company in year t.[11] In line with the literature, we estimate the DLD system using iterative SUR-GLS (Considine and Mount, 1984; Considine, 1990) because of its invariance with respect to the choice of the normalizing input factor.

Throughout, we apply a special bootstrap procedure to consistently estimate confidence intervals for the model coefficients and the associated elasticities. The bootstrap is a block wild bootstrap, applied to the estimated residuals of the DLD's cost-share equations (Cameron et al., 2008). The resulting critical values and confidence intervals are robust to time series correlation and heteroskedasticity in the errors of the share equations, as well as to contemporaneous correlation between the error terms of different cost-share equations.[12] Our bootstrap is an extension of the bootstrap procedure proposed by Eakin et al. (1990), who already emphasized the need for substitution elasticities that are non-linear functions of the model parameters. In our setting, the need to account for heteroskedasticity, autocorrelation and contemporaneous cross-equation correlation provides additional motivation for using the bootstrap.

4.2. *Endogenous structural break*

Our way of estimating the DLD system of Section 3 extends the existing literature by allowing for structural change. We estimate the DLD model separately for a pre-crisis period and a (post-) crisis period. These two subperiods are identified by an endogenous-break test. This approach results in time-varying substitution elasticities.

The sup-Wald test proposed by Andrews (1993) is a natural candidate to test whether the DLD system is affected by structural change. This test is an extension of the traditional Chow and Quandt tests, which detect structural change at a given (exogenously determined) point in time (Chow, 1960; Quandt, 1960). The break year is *endogenously* determined by the sup-Wald test.

The sup-Wald test runs as follows. Given break year t^*, (5) is estimated for the subsamples $t_{start} - (t^* - 1)$ and $t^* - t_{end}$.[13] For each possible break year t^*, we estimate the DLD system for the two subsamples determined by that break year. The coefficients of the DLD system are

[11]About 85-90% of U.S. Commercial banks is part of a bank holding company. Source: Call Reports 2000 – 2013.

[12]More specifically, the bootstrap is based on block-bootstrapping the residuals of the DLD model. It resamples the residuals over groups using blocks that contain all T observations for the chosen group. The resampled blocks are the same in each share equation to allow for contemporaneous correlation between the error terms of different cost-share equations.

[13]In the second sample we use the year $t^* - 1$ to obtain the values of the lagged input quantity.

allowed to differ across the two subsamples. Given M possible break years, we thus obtain M Wald statistics. The sup-Wald statistic is obtained as the largest Wald statistic over each of the M possible break points. Furthermore, the value of t^* at which the maximum occurs is the potential break year.

To obtain accurate finite-sample critical values for the sup-Wald test, we do not rely on the critical values tabulated by Andrews (1993). Instead, we proceed as in Diebold and Chen (1996) and use the bootstrap approach under the null hypothesis of structural stability to obtain critical values and p-values. The latter values can be used to determine the statistical significance of the structural break in the year with the largest Wald statistic. Once a significant structural break has been detected, the DLD system and the associated elasticities can be estimated for the resulting two subsamples.[14]

4.3. Oaxaca-Blinder decomposition

The expressions for the substitution elasticities in Equation (6) involve both model coefficients (β^*_{jk} and λ) and cost shares ($\bar{w}_k$). Hence, changes in substitution elasticities over time are due to changes in cost technology or or economic conditions. We apply an Oaxaca-Blinder decomposition to assess the relative importance of these two sources of change (Oaxaca, 1973; Blinder, 1973; Frondel and Schmidt, 2006). Assuming that the sup-Wald test identifies a break year, the Oaxaca-Blinder decomposition divides the change in elasticities after the break year into two counterfactual components: one that indicates how the ease of substitution is affected by the observed variation in economic conditions (given the same initial cost technology) and one that reflects the change due to changes in the cost technology (given the same economic conditions).

The Oaxaca-Blinder decomposition works as follows. We write the SR elasticity (evaluated in the average cost shares) as $E^{SR}_{jk} = E^{SR}_{jk}(\eta, \bar{w})$ to emphasize its dependence on η (the parameter vector of the underlying DLD system) and $\bar{w}$ (the vector of average cost shares). Let $\eta^{(0)}$ and $\bar{w}^{(0)}$ refer to the first subsample and $\eta^{(1)}$ and $\bar{w}^{(1)}$ to the second subsample. We can write

$$\underbrace{E^{SR}_{jk}(\eta^{(1)}, \bar{w}^{(1)}) - E^{SR}_{jk}(\eta^{(0)}, \bar{w}^{(0)})}_{\text{total difference}} = \underbrace{[E^{SR}_{jk}(\eta^{(1)}, \bar{w}^{(1)}) - E^{SR}_{jk}(\eta^{(1)}, \bar{w}^{(0)})]}_{\text{same cost parameters, different cost shares}} + \underbrace{[E^{SR}_{jk}(\eta^{(1)}, \bar{w}^{(0)}) - E^{SR}_{jk}(\eta^{(0)}, \bar{w}^{(0)})]}_{\text{same cost shares, different cost parameters}}.$$

[14]We notice that there are statistical tests to locate multiple structural breaks during the sample period (e.g., Bai and Perron, 1998, 2003). Because only long samples allow for multiple breaks, we confine our analysis to the test for a single break point. Also, the global financial crisis provides an economic basis (as opposed to a purely statistical reason) for expecting a single "most significant" break point.

The first component on the right-hand side of the Oaxaca-Blinder decomposition reflects the impact of changes in economic conditions on the elasticity change. The second component captures the influence of changes in the cost technology. We use the same technique to decompose the difference in long-term substitution elasticities.

5. U.S. banking data

We use year-end Call Report data to create a sample of U.S. banks covering the years 1998 – 2013.[15] Although we are actually interested in estimating the DLD system over the years 2000 – 2013, we add the year 1999 because of the lagged quantity variable in the DLD system. We assume the same four-input and five-output production technology as in Section 3. We deflate all level variables by expressing them in prices of the year 2000 using the All Urban Consumer Price Index. In the supplementary material it is explained how the Call Report Data have been used to obtain the input and output quantities and prices.

We confine the analysis to commercial banks with a physical location in a U.S. state and subject to deposit-related insurance. We filter out bank-year observations with extreme input prices by removing observations that fall below the 1% sample quantile or exceed the 99% sample quantile. We also remove bank-year observations with inconsistent values. Because we are interested in bank behavior over time, we construct a balanced sample containing all banks with complete observations during the years 1998 – 2013. An unbalanced sample will result in subsamples that do not contain the same group of banks. A balanced sample, by contrast, ensures that any changes over time are truly due to changes in bank behavior and not due to dynamic selection and is in line with many other banking studies (Dinç, 2005; Akhigbe and McNulty, 2011; Jaremski and Rousseau, 2013; Cai et al., 2014). The balanced sample contains 3,361 unique banks and 47,054 bank-years. We will later confirm the representativeness of our balanced sample by means of a comparison with the unbalanced sample. The unbalanced sample contains 8,910 unique banks and 90,496 bank-years. In the sequel we will work with the balanced samples, unless explicitly mentioned otherwise. Sample statistics will be presented in the next section, after we have identified the structural break.

[15] All U.S. banks have reported financial data on a quarterly basis since the mid-1980s. We use annual data because the quarterly data contains a huge amount of missing observations, due to which it is very difficult to create a sufficiently long balanced sample. We therefore follow Koetter et al. (2012) and consider year-end data.

6. Empirical results

This section provides estimation results for the DLD system and the corresponding cross-price and own-price elasticities of demand.

6.1. *Endogenous structural break*

We start with estimating the DLD system using the balanced 2000 – 2013 sample, while allowing for a structural break around the start of the global financial crisis. In line with Andrews (1993), we allow for potential lead-lag effects of the crisis and thus consider five possible break years: $t^* = 2006, 2007, 2008, 2009, 2010$. We refer to Section 4.2 for the exact definition of break year.

To perform the sup-Wald test, we proceed as outlined in Section 4.2. The sup-Wald test detects a highly significant break for $t^* = 2009$, thus dividing the 2000 – 2013 period into a pre-crisis period (2000 – 2008) and a (post-) crisis period (2009 – 2013). The first and second panels of Table 2 provide sample statistics for the (un)balanced subsamples. The balanced and unbalanced samples do not substantially differ in terms of sample means, although the scale of banks in the balanced sample is a bit larger than in the unbalanced sample. This pattern may result from consolidations: acquired banks are not in the balanced sample, while acquiring banks (which were initially larger and became larger yet after consolidation) are. Turning back to the balanced sample, a comparison of the sample means over the two subperiods indicates a substantially larger bank scale in the second subsample, which can be explained from the consolidations that took place after the onset of the crisis (Dunn et al., 2015). We also observe a substantial decline in the prices and cost shares of purchased funds and core deposits after the onset of the crisis, which reflects the actions taken by the Fed to boost the U.S. economy. The cost share of labor services increased substantially after the onset of the crisis, mostly due to the much lower interest rates after the onset of the crisis.

6.2. *DLD system with common adjustment coefficient*

Because the full DLD system only worsens the value of the Akaike Information Criterion (AIC), we focus on the DLD model with common adjustment coefficient throughout. To illustrate the negligible impact of adding extra adjustment coefficients to the model, Table 3 reports the estimated adjustment coefficients for the two subperiods as selected by the sup-Wald test. We see that the values of λ_{jp} are close to zero for $j \neq p$ and that the λ_{jj} very little across share equations. Hence, the lag time is virtually the same across share equations. This result explains why the full DLD model does not lead to a better model in terms of the AIC. We therefore use the more parsimonious DLD model with common adjustment coefficient in our entire analysis.

6.3. Estimation results for the DLD system

We use Zellner's iterative SUR-GLS to estimate the DLD system separately for the two subperiods identified by the sup-Wald test. The associated system R^2 ranges between 0.91 – 0.96. The coefficients of the dummy variable that indicates whether a bank is part of a bank holding company has little significance across the three cost-share equations, suggesting limited cost-share heterogeneity across banks. The second column of Table 4 shows that the pre-crisis adjustment parameter $\hat{\lambda}$ (see Section 3.1) is significant and equals $\hat{\lambda} = 0.85$ ([0.58, 0.65]), corresponding to a half-life of 4.3 ([4.1, 4.5]) years. During the crisis sample, however, the value of $\hat{\lambda}$ is significantly *higher* and equal to $\hat{\lambda} = 0.90$ ([0.35,0.0.48]), corresponding with a median lag time of about 6.5 ([6.1,7.0]) years. Hence, we observe significantly *slower* adjustment of cost shares to changes in input prices after the onset of the crisis, thus confirming hypothesis **H3**. Banks' median lag time increased by more than 50% after the onset of the crisis; i.e., the decrease in lag time shows that the crisis made banks' response to input price changes more sluggish.

6.4. Elasticity estimates

Table 5 reports the estimated SR and LR own-price and cross-price substitution elasticities based on the DLD system.[16]

We start with a discussion of the pre-crisis period, during which all SR elasticities are relatively low in magnitude.[17] The LR elasticities are substantially higher. In particular, the LR cross-price elasticity between physical capital and labor services is relatively high. Investments in technology (in the form of ATMs, computers, online banking services and other technology) can allow fewer tellers and loan officers to serve the same number of bank customers. Alternatively, a bank that relies more on off-balance-sheet business could assign relatively more staff to managing such activities rather than to traditional retail banking activities that rely on brick-and-mortar offices. Furthermore, purchased funds are an elastic substitute for labor services. We can explain this finding by observing that a heavier reliance on purchased funds allows banks to

[16] We have used the sample means of the cost shares to calculate the elasticities according to Equation (6).

[17] We notice that the own-price elasticities of demand are all negative due to the quasi-concavity that turns out to hold globally; i.e., the DLD system's eigenvalues are non-positive.

generate the same amount of earning assets with a smaller amount of core deposits, thus economizing on bank tellers (as well as branch offices and ATMs) needed to attract and retain core deposits. We also observe that, in the LR, purchased funds and core deposits are unit elastic substitutes. As explained in Section 2, it is evident that purchased funds and core deposits can act as substitutes. However, we observe a notable asymmetry here: purchased funds are much more elastic with respect to core deposits than vice versa. A possible explanation for this asymmetry is banks' limited influence on depositor behavior (Noulas et al., 1990). The remaining LR cross-price elasticities are relatively low. The cross-price elasticities related to deposits and labor services are the only negative ones. The latter two inputs turn out highly inelastic complements. As explained in Section 2, more deposits could require more loan officers to allocate the funds efficiently. In sum, we observe that most input factors tend to be inelastic substitutes, both in the SR and the LR. This result is in line with earlier studies on U.S. banks' substitution elasticities, such as Noulas et al. (1990) and Hunter and Timme (1995).[18] It is also consistent with the properties of the bank production function discussed in Section 2.

Table 5 shows that most substitution elasticities are smaller in magnitude after the onset of the crisis, especially in the LR. Hence, we confirm hypothesis **H1**. The associated Oaxaca-Blinder decomposition is displayed in Table 6, together with bootstrap-based confidence intervals. Table 6 shows that the elasticity drop is generally due to a combination of changes in economic conditions and changes in the cost technology. Only a few elasticities exhibit a significant increase after the onset of the crisis. In the SR, this holds for the two cross-price elasticities with respect to core deposits and labor services. The latter two inputs are highly inelastic complements before the crisis, but become perfectly inelastic after the onset of the crisis (with cross-price elasticities that are no longer significantly different from zero). Also before the crisis the substitutability of these two inputs is extremely low, so the economic relevance of the change is only minor. In the LR, the cross-price elasticities of physical capital and labor increase after the onset of the crisis. While the increase in the cross-price elasticity of labor services with respect to physical capital is economically speaking modest, the rise in the cross-price elasticity of physical capital with respect to labor services is both statistically and

[18]In their study of U.S. banks, Hunter and Timme (1995, Table 2) obtain substitution elasticities from two different specifications: a SR restricted variable cost function and a LR total cost function based on the restrictive assumption that input factors are observed at their LR equilibrium levels. They establish substantial quantitative differences in the substitution elasticities between the two models. The differences between SR and LR elasticities that we find are in line with the more ad hoc results of Hunter and Timme (1995) and once more emphasize the need to employ dynamic cost models.

economically substantial. Hence, while the crisis reduced the substitutability of most pairs of input factors, the latter LR elasticity exhibits a substantial rise after the onset of the crisis. From the Oaxaca-Blinder decomposition we see that the increase in the LR cross-price elasticity of physical capital with respect to labor services is due to changes in the economic conditions, which offsets the decrease due to changes in the cost parameters. The most prominent change in economic conditions here is the decrease in interest rates, which resulted in a mechanical increase in the cost share of labor services after the onset of the crisis (see Table 2).

The generally low degree of substitutability among banks' input factors (especially after the onset of the crisis) implies that there are only limited opportunities for banks to mitigate an increase in total costs due to an increase in one or more input prices. However, three elasticities remain relatively high after the onset of the crisis, especially in the LR. Besides the aforementioned elasticity of physical capital with respect to labor services, these are the elasticity of purchased funds with respect to labor services (which is not significantly different from unity in the LR, reflecting perfectly elastic substitutes) and the elasticity of purchased funds with respect to core deposits (which is significantly less than unity in the LR, but still relatively high). Hence, after the onset of the crisis banks could exert some control over their costs by substituting labor for physical capital and purchased funds, and core deposits for purchased funds.

6.5. The role of bank size

Section 2 addressed the potential influence of bank size on the substitutability of banks' input factors. To investigate the impact of bank size on the change in elasticities after the onset of the crisis, we have considered the full sample period and estimated an extended version of the DLD model. In this extended specification the coefficients depend on both time and bank size. In this way, the extended DLD system captures both time-varying and bank size-dependent substitution elasticities and adjustment coefficients. The details about the extended specification used to test hypothesis **H2** are in the appendix with supplementary material. The estimated coefficients of the interaction variables involving bank size do not turn out significant. Consequently, the effect of bank size on the substitution elasticities is only minor and we thus reject hypothesis **H2**. We notice that Noulas et al. (1990) found certain elasticity differences between small and large banks, but no systematic ones. The lack of such systematic differences is confirmed by our results and could reflect the fact that all banks face fundamentally the same production technology for traditional core banking activities (i.e., taking deposits and making loans) as we observed in Section 2. Although the largest banks heavily rely on trading activities and off-balance-sheet activities, it is possible that this does not show up in the estimation results because the sample of banks is dominated by smaller banks with a more traditional focus.

7. Robustness checks

As a robustness check, we have compared the DLD system with three alternative demand systems: the static translog, the dynamic translog and the static logit. Dynamic translog demand (DTD) systems are dynamic extensions of the well-known static translog model (Holly and Smith, 1989; Friesen, 1992b; Allen and Urga, 1999; Esho and Sharpe, 1995; Urga, 1999; Urga and Walters, 2003). The appendix with supplementary material provides a detailed description of the DTD system of Allen and Urga (1999), Urga (1999) and Urga and Walters (2003). The (dynamic) translog and logit demand systems are not nested. Consequently, information criteria such as those of Akaike or Schwarz cannot be used to compare the goodness-of-fit of the two models. However, we can make a qualitative comparison between the two systems based on their theoretical properties and a quantitative comparison based on both systems' estimation results. The qualitative comparison is in the appendix with supplementary material. The quantitative comparison is made below. It is important to notice that the LR elasticities provided by the DLD system are based on the conventional static translog cost function. Many studies estimating substitution elasticities are based on a similar cost function.

For the quantitative comparison we have estimated a DTD system for both the pre-crisis and the (post-) crisis samples, using Zellner's iterated SUR-GLS again.[19] The estimation results can be found in the appendix with supplementary material. The estimated adjustment parameter of the DTD system is significant at the 5% level during both subperiods and confirms the presence of lagged adjustment of the demand for inputs to changes in input prices. The associated average substitution elasticities are displayed in Table 7, together with 95% confidence intervals based on the bootstrap. Table 7 reveals multiple violations of the *Le Chatelier* principle. Because the elasticities in the DTD system take the form of ratios that have one or more cost shares in the denominator, very large elasticities can arise when cost shares are close to zero. This becomes most apparent during the pre-crisis period, when the elasticities related to changes in the input factor with the smallest cost share (physical capital) have very confidence intervals (resulting in elasticities that are not significantly different from 0). In the pre-crisis sample, the SR (LR) own-price physical capital's own-price elasticity is positive in 6% (7%) of

[19]The sup-Wald test applied to the DTD system detects a structural break in $t^* = 2009$.

the bank-year observations, reflecting the violation of quasi-concavity. The average own-price substitution elasticity for physical capital in Table 7 still has the required negative sign despite these positive observations, but this is merely due to the many negative outliers. Negative cost shares for physical capital occur in 17% of the bank-year observations in the pre-crisis sample. Because the translog demand systems do not satisfy the required theoretical properties, it is difficult to give an economically sensible interpretation to the associated elasticities.

To analyze the impact of ignoring the lagged adjustment of the demand for inputs to changes in input prices, we have also estimated a static logit demand (SLD) system for both the crisis and the (post-) crisis samples.[20] During both periods, the R^2 of the two static demand systems is much lower than that of the corresponding dynamic logit demand system (0.56 and 0.74 vs. 0.91 and 0.95). The corresponding static elasticities do not exhibit much of a change after the onset of the crisis.[21] Hence, if we had used the static demand system, we would have falsely concluded that the substitution elasticities had hardly changed after the onset of the crisis, emphasizing the need for dynamic demand systems.

Finally, we have also estimated the DLD system using the unbalanced data set. This leads to elasticities that are very similar as the ones we obtained on the basis of the balanced dataset. Furthermore, we have redone the entire analysis using Morishima elasticities, thereby focusing on relative instead of absolute substitutability of input factors. Most Morishima elasticities also exhibit a significant drop in magnitude after the onset of the crisis.

More details about the robustness checks are given in the appendix with supplementary material.

8. Conclusions

For banks, cost management has gained importance in the current environment of low interest rates. In this climate, banks' revenues from interest are under pressure, resulting in renewed interest in the substitutability of banks' input factors. This study has estimated U.S. commercial banks' substitution elasticities during the 2000 – 2013 period to analyze the total effects of the policy and technological change on banks' substitution elasticities during that period. An endogenous-break test divides the sample into a pre-crisis period (2000 – 2008) and a crisis period (2009 – 2013). During both periods most input factors turn out inelastic substitutes, both

[20] The sup-Wald test applied to the SLD system detects a structural break in $t^* = 2009$.

[21] To save space these elasticities are not reported. They are available upon request.

in the short run and the long run. Banks' median lag time increases by more than 50% after the onset of the crisis (from 4.3 to 6.5 years), which shows that banks respond more sluggishly to input price changes after the onset of the crisis. The short-run and long-run substitutability of most input factors decreases significantly due to a combination of changes in cost technology and economic circumstances. Hence, the overall effect of the policy, regulatory and technological changes on banks' substitution elasticities is mostly negative, especially in the long run. The degree of substitutability among banks' input factors is generally low after the onset of the crisis, providing only little room for cost management on the basis of input factor substitutability.

The finding of a statistically distinct breakpoint concurrent with the onset of the crisis strongly suggests that it was the crisis itself, rather than a coincident flow of confounding factors, that drove the observed decrease in substitution elasticities. The dramatic policy responses to the crisis – in both regulatory and monetary policy – seem likely candidates to underlie the elasticity changes. This reasoning is consistent with the findings of Noulas et al. (1990) that deregulation was associated with subsequently higher degrees of substitutability among bank input factors. Furthermore, it suggests that the associated hindrance to cost optimization is another component of regulatory burden and welfare loss. Although some restoration of pre-crisis elasticities might be attained by the simple expedient of partially relaxing some of the new policies, it seems unlikely that such a rigorous measure (if possible at all) will eventually be effective. That is, pre-crisis substitutability was already low (according to our and existing studies), suggesting that policies to increase banks' substitution elasticities to much higher levels are simply not easily available, or that attaining high substitution elasticities has not been a policy goal historically.

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Table 1: Aggregate Trends in Selected Balance-Sheet Items

Year	Federal Funds Sold	Federal Funds Purchased	Borrowed Funds	Total Deposits	Total Assets
2000	280	475	1,047	4,180	6,246
2001	318	503	1,072	4,378	6,552
2002	312	572	1,171	4,690	7,077
2003	332	528	1,261	5,035	7,601
2004	385	578	1,316	5,597	8,420
2005	443	668	1,425	6,078	9,047
2006	530	720	1,590	6,736	10,098
2007	646	766	1,882	7,314	11,182
2008	688	804	2,079	8,086	12,313
2009	402	551	1,483	8,337	11,827
2010	454	529	1,449	8,518	12,069
2011	458	439	1,193	9,259	12,650
2012	506	427	1,140	10,012	13,388
2013	424	337	1,109	10,386	13,673
2014	356	294	1,195	10,939	14,475

Note: Dollar figures are in billions of USD for all U.S. commercial banks. *Source:* FDIC, Historical Statistics on Banking.

Table 2: Sample statistics

	unbalanced			balanced		
	2000 – 2013	2000 – 2008	2009 – 2013	2000 – 2013	2000 – 2008	2009 – 2013
price of purchased funds (P_1)	**3.3%**	**4.0%**	**1.9%**	**3.3%**	**4.0%**	**1.9%**
	1.6%	1.4%	1.0%	1.6%	1.3%	1.0%
price of core deposits (P_2)	**1.8%**	**2.2%**	**0.8%**	**1.7%**	**2.2%**	**0.8%**
	1.1%	1.0%	0.5%	1.0%	0.9%	0.5%
wage rate (P_3)	**46.4**	**45.2**	**48.7**	**44.4**	**43.3**	**46.4**
	13.6	12.8	14.1	11.1	10.5	11.7
price of physical capital (P_4)	**34.9%**	**34.7%**	**34.2%**	**31.1%**	**31.3%**	**30.6%**
	35.2%	33.8%	35.3%	25.7%	25.1%	26.7%
purchased funds	**389,385**	**352,614**	**501,360**	**568,851**	**516,719**	**662,688**
	10,143,360	8,843,583	13,090,599	13,781,156	12,374,474	16,004,574
core deposits	**605,193**	**473,600**	**951,070**	**809,517**	**594,592**	**1,196,382**
	10,561,865	7,110,262	16,336,390	14,029,890	9,294,671	19,885,331
# full-time equiv. employees	**266.5**	**238.3**	**347.4**	**363.5**	**318.1**	**445.3**
	4,193	3,529	5,591	5,607	4,790	6,835
physical capital	**12,016**	**10,790**	**15,470**	**15,694**	**13,751**	**19,192**
	157,289	137,825	200,967	207,341	183,829	243,986
consumer loans (Y_1)	**91,036**	**75,067**	**132,715**	**114,699**	**99,114**	**142,754**
	1,997,441	1,602,241	2,739,784	2,409,783	2,135,570	2,837,206
business loans (Y_2)	**212,771**	**192,431**	**273,490**	**304,137**	**271,070**	**363,658**
	4,122,369	3,696,205	5,129,253	5,480,408	4,977,850	6,284,263
real estate loans (Y_3)	**366,857**	**322,823**	**486,126**	**472,955**	**391,906**	**618,842**
	5,742,327	4,693,702	7,836,373	7,590,142	6,204,257	9,591,293
securities (Y_4)	**216,838**	**166,922**	**350,504**	**289,885**	**211,762**	**430,506**
	4,044,764	2,710,703	6,285,750	5,304,788	3,524,933	7,510,031
off-balance sheet items (Y_5)	**17,619**	**15,011**	**24,797**	**25,145**	**20,879**	**32,823**
	393,771	319,563	541,359	522,944	429,330	658,682
cost share of core deposits (w_1)	**15.5%**	**16.8%**	**12.3%**	**14.7%**	**16.2%**	**12.1%**
	9.1%	9.4%	7.5%	8.5%	8.7%	7.4%
cost share of purchased funds (w_2)	**29.6%**	**34.5%**	**18.4%**	**29.2%**	**35.1%**	**18.4%**
	13.3%	11.7%	9.4%	13.3%	11.3%	9.2%
cost share of labor (w_3)	**44.1%**	**38.9%**	**56.1%**	**45.3%**	**39.0%**	**56.5%**
	13.8%	11.1%	11.8%	13.7%	10.4%	11.5%
cost share of physical capital (w_4)	**10.8%**	**9.8%**	**13.1%**	**10.9%**	**9.7%**	**13.0%**
	4.5%	4.1%	4.7%	4.4%	3.8%	4.6%
total costs (TC)	**38,234**	**38,894**	**38,568**	**51,617**	**52,825**	**49,444**
	694,302	710,223	681,954	925,159	972,341	833,551
# banks	8,554	8,169	5,723	3,361	3,361	3,361
# years	14	9	5	14	9	5
# bank years	90,116	62,433	26,343	47,054	30,249	16,805

Notes: This table reports sample statistics for balanced and unbalanced samples covering the full sample period (2000 – 2013), the pre-crisis period (2000 – 2008) and the (post-) crisis sample (2009 – 2013). All level variables have been deflated and are expressed in prices of the year 2000, in units of $ 1000. Ratio variables are expressed in %.

Table 3: Estimated adjustment matrix

	2000 – 2008			**2009 – 2013**		
	p.e.	**2.5%**	**97.5%**	**p.e.**	**2.5%**	**97.5%**
λ_{11}	0.8393	0.8322	0.8463	0.8832	0.8752	0.8906
λ_{12}	-0.0411	-0.0460	-0.0363	-0.0130	-0.0182	-0.0080
λ_{13}	-0.0388	-0.0431	-0.0346	-0.0118	-0.0164	-0.0077
λ_{22}	0.8541	0.8462	0.8619	0.9106	0.9036	0.9174
λ_{23}	-0.0290	-0.0359	-0.0221	-0.0282	-0.0345	-0.0217
λ_{33}	0.8123	0.8010	0.8226	0.8829	0.8735	0.8916

Notes: This table reports point estimates (p.e.) and 95% confidence intervals (2.5%: lower bound of confidence interval; 97.5%: upper bound of confidence interval) for the symmetric adjustment matrix (with zero row-sums) in the extended the DLD system applied to the pre-crisis sample (2000 – 2008) and the (post-) crisis sample (2009 – 2013). The confidence intervals are based on the bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations.

Table 4: Estimation results for DLD systems

	2000 – 2008			2008 – 2013		
	p.e.	**2.5%**	**97.5%**	**p.e.**	**2.5%**	**97.5%**
β^*_{12}	-0.5601	-0.5885	-0.5302	-0.6662	-0.7006	-0.6328
β^*_{13}	-0.5687	-0.5952	-0.5428	-0.8067	-0.8225	-0.7902
β^*_{14}	-0.6771	-0.7241	-0.6376	-0.8842	-0.9195	-0.8456
β^*_{23}	-1.0261	-1.0362	-1.0166	-0.9952	-1.0027	-0.9859
β^*_{24}	-0.9115	-0.9300	-0.8918	-0.9281	-0.9483	-0.9084
β^*_{34}	-0.7169	-0.7378	-0.6948	-0.8339	-0.8473	-0.8212
$interc_1$	-0.8329	-0.9420	-0.7271	-0.3645	-0.4831	-0.2557
γ_{11}	-0.0093	-0.0148	-0.0038	0.0086	0.0033	0.0139
γ_{12}	0.0141	0.0083	0.0206	0.0056	-0.0006	0.0117
γ_{13}	0.0474	0.0401	0.0549	0.0068	-0.0011	0.0148
γ_{14}	0.0080	0.0028	0.0136	0.0028	-0.0031	0.0080
γ_{15}	-0.0283	-0.0345	-0.0228	-0.0288	-0.0350	-0.0225
δ_{11}	0.0907	0.0759	0.1079	0.2205	0.2032	0.2385
δ_{12}	0.0207	0.0069	0.0358	0.1458	0.1302	0.1627
δ_{13}	-0.1437	-0.1580	-0.1301	0.1637	0.1479	0.1795
δ_{14}	-0.1561	-0.1691	-0.1426	0.0282	0.0140	0.0409
δ_{15}	-0.1613	-0.1750	-0.1462			
δ_{16}	-0.0487	-0.0621	-0.0347			
δ_{17}	0.0404	0.0275	0.0533			
δ_{18}	0.0347	0.0231	0.0469			
$BHC.dum_1$	0.0154	0.0018	0.0305	-0.0054	-0.0221	0.0110
$interc_2$	0.7932	0.7173	0.8717	0.6196	0.5293	0.6997
γ_{21}	-0.0125	-0.0165	-0.0084	-0.0070	-0.0108	-0.0034
γ_{22}	0.0170	0.0125	0.0214	0.0173	0.0135	0.0213
γ_{23}	0.0171	0.0116	0.0228	-0.0010	-0.0061	0.0042
γ_{24}	0.0093	0.0050	0.0134	0.0072	0.0040	0.0107
γ_{25}	-0.0258	-0.0303	-0.0212	-0.0158	-0.0205	-0.0119
δ_{21}	0.0330	0.0208	0.0451	0.0767	0.0647	0.0885
δ_{22}	0.0591	0.0476	0.0706	0.0646	0.0540	0.0758
δ_{23}	0.0076	-0.0032	0.0175	0.0585	0.0497	0.0674
δ_{24}	-0.0187	-0.0288	-0.0086	0.0447	0.0370	0.0529
δ_{25}	-0.0613	-0.0720	-0.0505			
δ_{26}	-0.0543	-0.0655	-0.0430			
δ_{27}	-0.0277	-0.0374	-0.0178			
δ_{28}	0.0002	-0.0090	0.0097			
$BHC.dum_2$	-0.0072	-0.0187	0.0044	-0.0090	-0.0219	0.0040
$interc_3$	0.3855	0.3136	0.4647	0.3991	0.3362	0.4630
γ_{31}	-0.0037	-0.0069	-0.0003	-0.0045	-0.0078	-0.0014
γ_{32}	0.0041	0.0007	0.0077	0.0039	0.0004	0.0076
γ_{33}	0.0022	-0.0025	0.0068	-0.0016	-0.0064	0.0033
γ_{34}	-0.0036	-0.0069	-0.0002	-0.0058	-0.0087	-0.0027
γ_{35}	-0.0018	-0.0054	0.0019	0.0039	-0.0004	0.0079
δ_{31}	0.0333	0.0222	0.0449	0.0094	-0.0015	0.0203
δ_{32}	0.0226	0.0117	0.0331	0.0063	-0.0030	0.0158
δ_{33}	0.0280	0.0182	0.0373	0.0141	0.0060	0.0229
δ_{34}	0.0131	0.0030	0.0222	-0.0020	-0.0108	0.0064
δ_{35}	0.0059	-0.0043	0.0158			
δ_{36}	0.0129	0.0029	0.0227			
δ_{37}	0.0143	0.0055	0.0233			
δ_{38}	0.0349	0.0268	0.0435			
$BHC.dum_3$	-0.0084	-0.0181	0.0011	-0.0072	-0.0182	0.0042
λ	0.8501	0.8429	0.8573	0.8995	0.8924	0.9059
system R^2	0.91			0.95		

Notes: This table reports point estimates (p.e.) and 95% confidence intervals (2.5%: lower bound of confidence interval; 97.5%: upper bound of confidence interval) for the DLD system applied to the pre-crisis sample (2000 – 2008) and the (post-) crisis sample (2009 – 2013). The coefficients correspond to (5). The coefficient of the indicator variable for being part of a bank holding company in cost share equation j is denoted by $BHC.dum_j$. The confidence intervals are based on the bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations.

Table 5: Substitution elasticities based on the DLD system

	SHORT RUN				*LONG RUN*			
	2000 – 2008							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.3541**	**0.1545**	**0.1684**	**0.0312**	**-2.3620**	**1.0306**	**1.1231**	**0.2082**
L	-0.3705	0.1445	0.1580	0.0267	-2.5045	0.9538	1.0495	0.1768
U	-0.3374	0.1650	0.1784	0.0350	-2.2286	1.1109	1.2042	0.2368
CD	**0.0712**	**-0.0695**	**-0.0102**	**0.0086**	**0.4748**	**-0.4638**	**-0.0681**	**0.0571**
L	0.0666	-0.0745	-0.0141	0.0068	0.4394	-0.4991	-0.0945	0.0452
U	0.0760	-0.0646	-0.0065	0.0105	0.5118	-0.4319	-0.0436	0.0691
LS	**0.0698**	**-0.0092**	**-0.0880**	**0.0274**	**0.4656**	**-0.0613**	**-0.5869**	**0.1826**
L	0.0655	-0.0127	-0.0941	0.0253	0.4351	-0.0850	-0.6230	0.1720
U	0.0740	-0.0058	-0.0826	0.0295	0.4992	-0.0392	-0.5547	0.1936
PC	**0.0522**	**0.0311**	**0.1105**	**-0.1938**	**0.3485**	**0.2073**	**0.7372**	**-1.2930**
L	0.0446	0.0246	0.1023	-0.2025	0.2959	0.1643	0.6944	-1.3365
U	0.0586	0.0380	0.1191	-0.1855	0.3963	0.2511	0.7819	-1.2548
	2009 – 2013							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.1857**	**0.0614**	**0.1091**	**0.0151**	**-1.8481**	**0.6115**	**1.0864**	**0.1501**
L	-0.1989	0.0551	0.1002	0.0105	-2.0083	0.5416	0.9784	0.1023
U	-0.1734	0.0676	0.1185	0.0201	-1.6970	0.6811	1.2017	0.2010
CD	**0.0404**	**-0.0525**	**0.0027**	**0.0094**	**0.4023**	**-0.5223**	**0.0268**	**0.0932**
L	0.0363	-0.0570	-0.0016	0.0067	0.3563	-0.5790	-0.0148	0.0686
U	0.0445	-0.0482	0.0080	0.0119	0.4480	-0.4733	0.0795	0.1169
LS	**0.0234**	**0.0009**	**-0.0459**	**0.0216**	**0.2330**	**0.0087**	**-0.4571**	**0.2154**
L	0.0215	-0.0005	-0.0488	0.0199	0.2098	-0.0048	-0.4949	0.2011
U	0.0254	0.0026	-0.0431	0.0233	0.2577	0.0259	-0.4222	0.2290
PC	**0.0140**	**0.0132**	**0.0938**	**-0.1210**	**0.1395**	**0.1317**	**0.9336**	**-1.2048**
L	0.0098	0.0095	0.0862	-0.1288	0.0951	0.0970	0.8718	-1.2543
U	0.0187	0.0169	0.1010	-0.1135	0.1868	0.1651	0.9926	-1.1570

Notes: This table displays point estimates and 95% confidence intervals for the SR and LR own-price and cross-price elasticities based on (5). The elasticity's point estimates are given in bold face. The lower ('L') and upper ('U') bounds of the associated 95% confidence intervals are given in normal font. The confidence intervals are based on the bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations. The input factors in the rows of the table refer to the input factor whose demand changes in response to a % change in the price of the input factor in the columns of the table. For example, the elasticity in the row captioned 'PF' and the column captioned 'CD' refers to the % change in purchased funds, in response to a % change in core deposits. Abbreviations: PF = purchased funds; CD = core deposits; LS = labor services; PC = physical capital.

Table 6: Oaxaca-Blinder decomposition of differences in substitution elasticities (2000 – 2008 vs. 2009 – 2013)

	SHORT RUN			*LONG RUN*		
	diff	**diff.ec**	**diff.tech**	**diff**	**diff.ec**	**diff.tech**
PF-PF	**0.1684**	**0.0182**	**0.1502**	**0.5139**	**0.1813**	**0.3326**
L	0.1503	0.0124	0.1303	0.3285	0.1232	0.1294
U	0.1866	0.0242	0.1695	0.7013	0.2408	0.5504
PF-CD	**-0.0931**	**-0.0558**	**-0.0373**	**-0.4191**	**-0.5554**	**0.1363**
L	-0.1033	-0.0614	-0.0514	-0.5197	-0.6185	-0.0107
U	-0.0824	-0.0501	-0.0227	-0.3246	-0.4919	0.2816
PF-LS	**-0.0592**	**0.0337**	**-0.0929**	**-0.0367**	**0.3354**	**-0.3721**
L	-0.0718	0.0309	-0.1043	-0.1552	0.3020	-0.4688
U	-0.0473	0.0366	-0.0824	0.0846	0.3710	-0.2741
PF-PC	**-0.0161**	**0.0039**	**-0.0200**	**-0.0581**	**0.0387**	**-0.0968**
L	-0.0221	0.0027	-0.0251	-0.1102	0.0264	-0.1397
U	-0.0102	0.0052	-0.0150	-0.0055	0.0518	-0.0539
CD-PF	**-0.0308**	**-0.0136**	**-0.0172**	**-0.0726**	**-0.1353**	**0.0628**
L	-0.0361	-0.0150	-0.0237	-0.1300	-0.1507	-0.0049
U	-0.0252	-0.0122	-0.0104	-0.0186	-0.1199	0.1297
CD-CD	**0.0171**	**0.0103**	**0.0067**	**-0.0585**	**0.1030**	**-0.1615**
L	0.0114	0.0078	0.0011	-0.1186	0.0788	-0.2260
U	0.0230	0.0126	0.0131	-0.0008	0.1261	-0.0968
CD-LS	**0.0129**	**0.0008**	**0.0121**	**0.0949**	**0.0083**	**0.0866**
L	0.0076	-0.0005	0.0076	0.0489	-0.0046	0.0508
U	0.0183	0.0025	0.0165	0.1488	0.0246	0.1255
CD-PC	**0.0008**	**0.0024**	**-0.0016**	**0.0361**	**0.0240**	**0.0121**
L	-0.0021	0.0017	-0.0041	0.0106	0.0177	-0.0081
U	0.0035	0.0031	0.0007	0.0608	0.0301	0.0310
LS-PF	**-0.0464**	**-0.0079**	**-0.0385**	**-0.2326**	**-0.0784**	**-0.1542**
L	-0.0509	-0.0085	-0.0432	-0.2683	-0.0867	-0.1943
U	-0.0423	-0.0072	-0.0342	-0.1990	-0.0706	-0.1137
LS-CD	**0.0101**	**-0.0008**	**0.0109**	**0.0700**	**-0.0079**	**0.0779**
L	0.0066	-0.0024	0.0068	0.0453	-0.0235	0.0457
U	0.0134	0.0005	0.0149	0.0951	0.0044	0.1129
LS-LS	**0.0421**	**0.0031**	**0.0390**	**0.1298**	**0.0308**	**0.0990**
L	0.0367	0.0017	0.0332	0.0899	0.0166	0.0462
U	0.0479	0.0047	0.0452	0.1707	0.0484	0.1491
LS-PC	**-0.0057**	**0.0056**	**-0.0113**	**0.0328**	**0.0556**	**-0.0227**
L	-0.0085	0.0051	-0.0138	0.0164	0.0519	-0.0369
U	-0.0032	0.0060	-0.0090	0.0483	0.0591	-0.0095
PC-PF	**-0.0382**	**-0.0047**	**-0.0335**	**-0.2090**	**-0.0469**	**-0.1620**
L	-0.0458	-0.0063	-0.0421	-0.2725	-0.0628	-0.2338
U	-0.0303	-0.0033	-0.0251	-0.1453	-0.0320	-0.0903
PC-CD	**-0.0179**	**-0.0120**	**-0.0058**	**-0.0757**	**-0.1196**	**0.0439**
L	-0.0251	-0.0153	-0.0148	-0.1275	-0.1500	-0.0295
U	-0.0108	-0.0086	0.0027	-0.0256	-0.0881	0.1127
PC-LS	**-0.0167**	**0.0290**	**-0.0457**	**0.1965**	**0.2882**	**-0.0917**
L	-0.0283	0.0266	-0.0559	0.1267	0.2691	-0.1488
U	-0.0064	0.0312	-0.0365	0.2629	0.3064	-0.0382
PC-PC	**0.0728**	**-0.0122**	**0.0850**	**0.0882**	**-0.1217**	**0.2099**
L	0.0620	-0.0163	0.0747	0.0293	-0.1636	0.1450
U	0.0836	-0.0083	0.0969	0.1423	-0.0820	0.2742

Notes: This table provides an Oaxaca-Blinder decomposition for the difference in short-run and LR substitution elasticities between the pre-crisis and (post-) crisis periods. Three components are reported: the total difference ('diff'), the change due to changes in economic conditions ('diff.ec') and the difference due to changes in the cost technology ('diff.tech'). The table displays both point estimates and 95% confidence intervals. The point estimates are given in bold face. The lower ('L') and upper ('U') bounds of the associated 95% confidence intervals are given in normal font. The confidence intervals are based on the bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations. All underlying elasticity estimates are based on (3). Abbreviations: PF = purchased funds; CD = core deposits; LS = labor services; PC = physical capital. In the first column, $PC - LS$ refers to the substitution elasticity of physical capital with respect to a change in labor costs etc.

Table 7: Substitution elasticities based on the DTD system

	SHORT RUN				*LONG RUN*			
	2000 – 2008							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.7119**	**0.3334**	**0.4148**	**-0.0363**	**-0.6735**	**0.3135**	**0.4114**	**-0.0514**
L	-0.8194	0.2596	0.2973	-0.0929	-0.8107	0.2125	0.2564	-0.1271
U	-0.6018	0.4110	0.5133	0.0187	-0.5233	0.4121	0.5406	0.0193
CD	**0.1380**	**-0.3974**	**0.2437**	**0.0158**	**0.1338**	**-0.3407**	**0.1915**	**0.0155**
L	0.0963	-0.2953	0.0460	0.0000	0.0783	-0.1989	-0.0784	-0.0046
U	0.1575	-0.1767	0.1515	0.0316	0.1587	-0.0594	0.0564	0.0358
LS	**0.1487**	**0.0981**	**-0.2962**	**0.0494**	**0.1475**	**0.0113**	**-0.2174**	**0.0587**
L	0.1064	0.0781	-0.3505	0.0208	0.0923	-0.0287	-0.2825	0.0222
U	0.1857	0.1253	-0.2398	0.0721	0.1955	0.0439	-0.1297	0.0889
PC	**2.2079**	**0.5967**	**-3.1031**	**0.2984**	**2.7929**	**0.6518**	**-4.1078**	**0.6632**
L	-4.0322	-0.9317	-6.2318	-3.9636	-5.2010	-1.3668	-8.2373	-4.7464
U	3.9127	1.7976	7.3187	1.7137	5.1645	2.2916	9.4704	2.4603
	2009 – 2013							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.6151**	**0.2259**	**0.3953**	**-0.0060**	**-0.5085**	**0.2348**	**0.3028**	**-0.0291**
L	-1.1809	0.0865	-0.4360	-0.2023	-1.2682	0.0550	-0.8905	-0.3171
U	0.3565	0.4109	0.9038	0.1124	0.8945	0.5003	0.9880	0.1375
CD	**0.0706**	**-0.9215**	**0.7917**	**0.0593**	**0.0694**	**-0.9632**	**0.8352**	**0.0586**
L	0.0342	-0.6929	-0.2300	0.0316	0.0200	-0.6405	-0.5705	0.0211
U	0.1346	0.1119	0.5457	0.1041	0.1623	0.4189	0.4886	0.1205
LS	**0.0447**	**0.0975**	**-0.2162**	**0.0740**	**0.0347**	**0.0623**	**-0.1753**	**0.0783**
L	0.0328	0.0905	-0.2382	0.0576	0.0165	0.0465	-0.2018	0.0573
U	0.0590	0.1136	-0.2019	0.0895	0.0521	0.0786	-0.1483	0.0977
PC	**-0.0046**	**0.2174**	**0.8011**	**-1.0138**	**-0.0316**	**0.2234**	**0.8479**	**-1.0396**
L	-0.1288	0.1246	0.6200	-1.1908	-0.2081	0.0985	0.6015	-1.2869
U	0.1062	0.3150	1.0057	-0.8580	0.1202	0.3683	1.1420	-0.8231

Notes: This table displays the point estimates and 95% confidence intervals for the SR and LR own-price and cross-price elasticities, based on the DTD system. The elasticity's point estimates are given in bold face. The lower ('L') and upper ('U') bounds of the associated 95% confidence intervals are given in normal font. The confidence intervals are based on the bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations. The input factors in the rows of the table refer to the input factor whose demand changes in response to a % change in the price of the input factor in the columns of the table. For example, the elasticity in the row captioned 'PF' and the column captioned 'CD' refers to the % change in purchased funds, in response to a % change in core deposits. Abbreviations: PF = purchased funds; CD = core deposits; LS = labor services; PC = physical capital.