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Adapting to Changing Input Prices in Response to the Crisis: The Case of U.S. Commercial Banks

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Abstract

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Keywords

financial crisis, substitution elasticities, US commercial banks

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Adapting to Changing Input Prices in Response to the Crisis: The Case of U.S. Commercial Banks

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Abstract

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. Because the crisis has drastically altered the economic environment in which banks operate, we expect to find changes in banks' substitution patterns over time. This study uses a dynamic demand system to analyze U.S. commercial banks' substitution elasticities and adjustment time to input price changes during the 2000 – 2013 period. After the onset of the crisis, banks' response to input price changes became more sluggish and the substitutability of most input factors decreased significantly. Yet the substitutability of labor for physical capital rose remarkably, which we attribute to the continuing adoption of online banking technologies. Our results confirm that, with only few exceptions, the crisis has significantly reduced the substitutability of banks' input factors and thereby the possibilities for cost management. Nevertheless, we find that even after the onset of the crisis banks continued to control their costs by substituting labor for purchased funds and – to a lesser extent – labor for physical capital and core deposits for purchased funds. The results are consistent across banks of different sizes.

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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. For banks – whose typical input factors are purchased funds, core deposits, labor services and physical capital – positive substitution elasticities are also favorable for liability and liquidity management. For example, the supply of purchased funds is subject to market disruptions outside the bank's control and can therefore be relatively volatile. Consequently, the ability to substitute between purchased funds and core deposits might improve a bank's ability to control liquidity risk. Another motivation to study input price elasticities is the relation between changes in firms' substitution elasticities and firms' behavioral shifts in response to economic and regulatory changes (Considine, 1989b; Noulas et al., 1990; Pantalone and Platt, 1994; Stiroh, 1999; Steinbuks, 2012).

The goal of this study is to assess the effect of the crisis on U.S. commercial banks' substitution elasticities. 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). Because the crisis has drastically altered the environment in which banks operate, we expect to find changes in banks' substitution patterns over time (Noulas et al., 1990; Pantalone and Platt, 1994; Stiroh, 1999).

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; Mester, 1996; Hunter and Timme, 1995). 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 effect of the crisis on U.S. commercial banks' substitution elasticities, this study opts for a dynamic approach based on the 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 in empirical applications than the dynamic translog demand system (Jones, 1995; Urga and Walters, 2003). Motivated by its favorable properties, we use the DLD system to analyze U.S. commercial banks' SR and LR substitution elasticities and lag times during the period 2000 – 2013. 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.

Because the definition of the start of the crisis might affect the analysis (Mierau and Mink, 2013), we determine the pre-crisis and crisis sample endogenously using the 'sup-Wald' methodology of Andrews (1993). The sup-Wald test divides our sample into a pre-crisis sample (2000 – 2008) and a (post-)crisis sample (2009 – 2013). During the first period, banks' median lag time was about 4.3 years and most input factors were inelastic substitutes, both in the SR and the LR. Banks' median lag time increased by more than 50% after the onset of the crisis (to 6.5 years). The SR and LR substitutability of most input factors decreased significantly. Yet the substitutability of labor for physical capital rose remarkably, which we attribute to the continuing adoption of online banking technologies. Our results confirm that, with only few exceptions, the crisis has significantly reduced the substitutability of banks' input factors and thereby the possibilities for cost management. Nevertheless, we find that even after the onset of the crisis banks continued to control their costs by substituting labor for purchased funds and – to a lesser extent – labor for physical capital and core deposits for purchased funds. The results are consistent across banks of different sizes.

Both the static and the dynamic translog demand systems produce results that are difficult to interpret because they violate elementary economic laws. Moreover, if we had used a static logit demand system, we would have falsely concluded that the substitution elasticities had hardly changed after the onset of the crisis. Hence, our results emphasize the need to employ proper dynamic demand systems to estimate substitution elasticities.

The setup of the remainder of this study is as follows. Section 2 uses the existing literature to formulate several effects that we expect to find in our empirical analysis. 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

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.

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) can allow fewer tellers and loan officers to serve the same number of bank customers. There is also another reason why labor and physical capital might 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.

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 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.

Several 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. The effect of the crisis

The literature has associated changes in banks' and thrifts' substitution elasticities with behavioral shifts in response to economic and regulatory changes (Noulas et al., 1990; Pantalone and Platt, 1994; Stiroh, 1999). For example, Noulas et al. (1990) documents a higher degree of substitutability among bank input factors after deregulation. Also in other industries, economic and regulatory changes have been associated with changes in substitution elasticities; see e.g. Considine (1989b) and Steinbuks (2012) who analyze the changes in interfuel substitutability in response to policy changes.

Also the global financial crisis that started with the fall of Lehman Brothers in September 2008 is likely to have affected banks' substitution elasticities. That is, the crisis and the Federal Reserve's subsequent quantitative easing sharply altered banks' mix of inputs and outputs. 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, 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. 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). This exogenous change in pricing and market conduct should be expected to alter measurable characteristics of banks' cost functions, including both the elasticities of substitution among inputs and the lag time, though the directions of such changes are difficult to predict on purely theoretical grounds.

Historically, large U.S. banks have been net borrowers of federal funds while smaller banks have been net lenders. Thus, the reduction in aggregate federal funds purchased would be expected to show up among large banks disproportionately, while the reduction in aggregate federal funds sold (an asset-side item or output) should appear relatively more among smaller banks. This difference between small and large banks might show up in their substitution elasticities.

2.3. *Online banking*

One of the most notable technological shifts concurrent with, but largely unrelated to, 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.

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 particular, 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 alter empirical estimates of input substitution elasticities and lag times, further motivating assessment of a potential shift over time in our sample, though potentially confounding an interpretation of such shifts as due solely to the crisis rather than to technological factors.

2.4. *Expected effects*

Based on the literature and the discussion in Sections 2.2 and 2.3 above, we expect that banks' substitution elasticities changed after the onset of the financial crisis. As explained before, however, it is difficult to predict the changes in substitutability on purely theoretical grounds. More intuitively, we expect that the post-onset regulatory response resulted in reduced SR and LR substitutability among banks' input factors, reflecting the stressful environment of the crisis. At the same time we anticipate that the substitution of labor for physical capital continued to persist after the onset of the crisis, reflecting the continuing adoption of online banking. Hence, we expect the substitution elasticity of physical capital with respect to labor to remain relatively high over time.

Regarding banks' speed of adjustment to input price changes, we can think of two scenarios. On the one hand, financial stress could have made banks' response to input price changes more sluggish, resulting in a longer lag time. On the other hand, 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.

Because of the aforementioned differences between small and large banks, we expect to find differences in the way their input factor substitutability was affected following the crisis. However, it is not a priori clear what the sign and magnitude of this difference will be and whether it will apply to all input factors. We will leave this as an empirical question.

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 $i = 1, \dots, N$ in year $t = 1, \dots, T$ ($P_{1,it}$), 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 $k = 1, \dots, 4$. 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

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

To allow for differences in cost technology between independent banks and banks that are part of a bank-holding company, we follow Wheelock and Wilson (2012) and include a binary variable (BHC_{it}) indicating whether bank i is part of a bank holding company in year t.[1] Furthermore,

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

d_t is a time dummy for year t, α_j, β_{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

$$\begin{aligned}
\log(w_{j,it}/w_{4,it}) &= (\alpha_j - \alpha_4)BHC_{it} + \sum_{k=1}^{j-1}(\beta^*_{kj} - \beta^*_{k4})\bar{w}_j \log(P_{k,it}/P_{4,it}) \\
&+ \Big(-\sum_{k=1}^{j-1} \bar{w}_k\beta^*_{jk} - \sum_{k=j+1}^{4} \bar{w}_k\beta^*_{jk} - \bar{w}_j\beta^*_{j4}\Big)\log(P_{j,it}/P_{4,it}) \\
&+ \sum_{k=j+1}^{3}(\beta^*_{jk} - \beta^*_{k4})\bar{w}_k \log(P_{k,it}/P_{4,it}) \\
&+ \sum_{\ell=1}^{5}(\gamma_{j\ell} - \gamma_{4\ell})\log(Y_{\ell,it}) + \sum_{t=1}^{T}(\delta_{jt} - \delta_{4t})d_t + e_{j,it} - e_{4,it} \qquad [j = 1, 2, 3],
\end{aligned} \tag{3}$$

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

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

To achieve identification, each row of the matrix of adjustment coefficients $(\lambda_{jp})_{j,p}$ 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 $p = 1, 2, 3$ 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 specification search in our empirical example. We will therefore focus on this version of the DLD model in the sequel.

In Considine and Mount (1984) it is shown that the 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 use of this estimator is motivated in more detail in the appendix with supplementary material.

The literature has estimated 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).[2]

3.2. Substitution elasticities

We follow Frondel (2004, 2011) and focus on the own-price and cross-price elasticities of demand.[3] On the basis of the dynamic extension of (3), the SR elasticities take the form

$$E_{jj}^{SR} = \frac{\partial \log(Q_{j,it})}{\partial \log(P_{j,it})} = \bar{w}_j \beta_{jj}^{*} + \bar{w}_j - 1, \quad E_{jk}^{SR} = \frac{\partial \log(Q_{j,it})}{\partial \log(P_{k,it})} = \bar{w}_k \beta_{jk}^{*} + \bar{w}_k \qquad [j \neq k], \tag{5}$$

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

[2]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.

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

common adjustment coefficient λ can be expressed in terms of the SR elasticities and λ as

$$E_{jk}^{LR} = E_{jk}^{SR}/(1-\lambda). \tag{6}$$

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 $\lambda > 0$.

4. Estimation strategy

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.

4.1. Coefficients and confidence intervals

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.[4] Our bootstrap is an extension of the bootstrap procedure proposed by Eakin et al. (1990), who 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

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

[4]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.

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^*, the dynamic version of Equation (3) is estimated for the subsamples $t_{start} - (t^* - 1)$ and $t^* - t_{end}$.[5] 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 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 applied to panel data, we will 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.[6]

4.3. Oaxaca-Blinder decomposition

The expressions for the substitution elasticities in Equation (5) involve both model coefficients and cost shares. Hence, changes in substitution elasticities over time are due to changes in (average) cost shares $\bar{w}_k$ (reflecting changes in input mix/prices) or due to changes in the coefficients β^*_{jk} and λ of the DLD system. 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 input mix/prices (given the same initial cost parameters) and one that reflects the change due to changes in the cost parameters (given the same initial cost shares).

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

[6] We notice that there are tests to locate multiple structural breaks during the sample period (e.g., Bai and Perron, 1998, 2003). However, our samples are not sufficiently long to allow for multiple breaks and we therefore 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 Oaxaca-Blinder decomposition works as follows. We write the SR elasticity (evaluated in the average cost shares) as $E_{jk}^{SR} = E_{jk}^{SR}(\eta, \bar{w})$ 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

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

The first component on the right-hand side of the Oaxaca-Blinder decomposition reflects the impact of changes in input mix/prices on the elasticity change. The second component captures the influence of changes in the cost parameters. 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.[7] 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

[7] 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.

3,361 unique banks and 47,054 bank-years. Because survivorship bias is a potential problem for a balanced sample, 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 a structural break.

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. 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 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 wage rate increased after the onset of the crisis. This could be due to the lower-level personnel that was laid off because of the crisis or because of the adoption of online-banking technologies that made some of the personnel redundant. The average share of core deposits in total costs is substantially lower in the second subsample, while the average cost share of labor services is considerably higher during the latter period.

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. Banks' median lag time increased by more than 50% after the onset of the crisis. As conjectured in Section 2, 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.[8]

We start with a discussion of the pre-crisis period, during which all SR elasticities are relatively low in magnitude. The LR elasticities are substantially higher. For example, 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 generate the same amount of earning assets with a smaller amount of core deposits, thus economizing on bank tellers (as well as branch

[8]We have used the sample means of the cost shares to calculate the elasticities according to Equation (5).

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). Also 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. All other 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).[9] 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. This pattern reflects reduced input factor substitutability after the start of the crisis. 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 input mix/prices and changes in the cost parameters. 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

[9]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.

low, so the economic relevance of the change is only minor. In the LR, also 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 economically substantial. Hence, while the crisis reduced the substitutability of most pairs of input factors, the substitutability of labor services for physical capital exhibits a substantial rise after the onset of the crisis. From the Oaxaca-Blinder decomposition we see that the increase in the cross-price elasticity of physical capital with respect to labor services is due to changes in the input mix/prices, which offsets the decrease due to changes in the cost parameters. In the light of the discussion in Section 2, the latter increase is likely to reflect the continuing adoption of online banking technologies.[10]

The generally low degree of substitutability among banks' input factors implies that there are only limited opportunities for substituting inputs to mitigate an increase in total costs due to an increase in one or more input prices. This limits banks' possibilities for cost management. 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, even after the onset of the crisis banks continued to control their costs to some extent by substituting labor for physical capital and purchased funds, and core deposits for purchased funds.

6.5. Comparison to alternative demand systems

We compare the results based on 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. Con-

[10] 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.

sequently, 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.[11] 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 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.

7. Robustness checks

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

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

and the (post-)crisis samples.[12] 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 elasticities do not exhibit much of a change after the onset of the crisis.[13] 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.

In Section 2 we 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. However, the 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. 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.

We have also estimated the DLD system using the unbalanced dataset. This leads to elasticities that are very similar as the ones we obtained on the basis of the balanced dataset. Hence, survivorship bias does not seem to be an issue in this study.

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 of the robustness checks are given in the appendix with supplementary material.

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

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

8. Conclusions

We have estimated U.S. commercial banks' substitution elasticities during the period 2000 – 2013 using a dynamic logit input demand system. This system allows the demand for any input factor to adjust with a lag to input price changes, where the speed of adjustment (known as the lag time) is estimated from the data.

An endogenous-break test divided 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 in the short run and the long run. Banks' median lag time increased by more than 50% after the onset of the crisis (from 4.3 to 6.5 years), which shows that banks responded more sluggishly to input price changes after the onset of the crisis. The short-run and long-run substitutability of most input factors decreased significantly due to a combination of changes in the input mix/prices and changes in the cost parameters. Yet the substitutability of labor for physical capital rose remarkably due to changes in the input mix/prices, which we attribute to the continuing adoption of online banking technologies. The results are consistent across banks of different sizes.

Our results confirm that, with only few exceptions, the crisis has significantly reduced the substitutability of banks' input factors and thereby the possibilities for cost management. Nevertheless, we find that even after the onset of the crisis banks continued to control their costs by substituting labor for purchased funds and – to a lesser extent – labor for physical capital and core deposits for purchased funds.

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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
2014	356	294	1,198	10,953	14,494
2009	402	551	1,483	8,338	11,829
2008	688	804	2,079	8,082	12,309
2005	443	668	1,425	6,073	9,041
2000	280	475	1,047	4,180	6,246

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**
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%
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%
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
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%
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
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
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
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
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
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%
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%
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%
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%
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
ROA	**0.8%**	**0.9%**	**0.7%**	**1.0%**	**1.1%**	**0.8%**
	1.1%	1.0%	1.1%	0.7%	0.6%	0.8%
EQ/TA	**10.7%**	**10.6%**	**10.7%**	**10.6%**	**10.5%**	**10.7%**
	3.9%	3.9%	3.1%	3.0%	3.1%	2.7%
AC	**3.9%**	**4.3%**	**2.9%**	**3.8%**	**4.3%**	**2.8%**
	1.2%	1.1%	0.9%	1.2%	1.0%	0.8%
# 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 %. Abbreviations: P_i: price of input $i = 1, 2, 3, 4$ (1: purchased funds; 2: core deposits; 3: labor services; 4: physical capital); Y_k: level of output variable $k = 1, 2, 3, 4, 5$ (1: consumer loans; 2: real estate loans; 3: business and other loans; 4: securities; 5: off-balance sheet items); w_i: value of i-th cost share; TC: total costs; AC: average costs.

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 the dynamic version of the share equation system of Equation (3). 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 the dynamic version of the share equation system of Equation (3). 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
LC-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 the economic environment (‘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 the dynamic version of the share equation system of Equation (3). Abbreviations: PF = purchased funds; CD = core deposits; LS = labor services; PC = physical capital.

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.

ONLINE-ONLY APPENDIX WITH SUPPLEMENTARY MATERIAL

Contents

1. Call report data

Table 1 provides an overview of the variables used in the empirical analysis and the Call Report series that have been used to create them.

2. Properties and comparison

This appendix discusses the dynamic generalized translog demand system of Allen and Urga (1999) and Urga and Walters (2003) and provides the estimated model coefficients that were not reported in the main text.

2.1. Theoretical properties

The cost shares in a translog cost model may turn out negative. Several other limitations of the translog cost function – which are ironically due to its flexibility – become particularly apparent in the estimation of input price elasticities. The own-price elasticities of demand may become positive instead of negative, which happens if the cost function is not quasi-concave in certain points. Quasi-concavity holds if the matrix of second-order partial derivatives of cost is negative semi-definite and implies non-negative own-price elasticities. Violations of quasi-concavity have been reported in several translog studies; see e.g. Urga and Walters (2003) and Ogawa (2011). Violation of quasi-concavity is particularly likely for inputs with a small cost share, in the presence of limited substitution opportunities, or with a high relative input price variance (Considine, 1989a,b). Ogawa (2011) points out that substitution elasticities are biased if the observations violating quasi-concavity are not excluded from the analysis. When the estimated elasticities do not satisfy the required theoretical properties, their economic interpretation is unclear.

Thanks to their functional form, both the static and the dynamic logit demand systems have non-negative cost shares by definitions. The resulting conditional demand functions are degree-zero homogenous and symmetric in the observed cost shares. The non-negativity of the cost shares contributes to more stable concavity conditions relative to other functional forms such as the translog cost function. Furthermore, the share equations' exponential form makes normality more likely than in share equation models with additive errors. Additionally, the DLD system has the favorable property that the LR substitution elasticities are always larger in magnitude than their SR counterparts (provided that both are evaluated in the LR cost shares), implying that the *Le Chatelier* principle holds. Because the substitution elasticities based on the (dynamic) logit demand system behave according to the desired theoretical properties, their interpretation is straightforward.

2.2. Model description

We start with imposing, in the long-run, linear homogeneity in input prices by normalizing total costs and input prices with the price of purchased funds ($P_{1,it}$). Throughout, variables with a tilde have been normalized with the price of purchased funds prior to taking the logarithmic transformation. This results in the following *long-run* cost function for bank i in year t:

$$\begin{aligned}
\log(\widetilde{C}_{it}) \;=\;& \alpha_i + \sum_{j=2}^{4}\beta_{j,p}\log(\widetilde{P}_{j,it}) + (1/2)\sum_{j=2}^{4}\sum_{k=2}^{4}\beta_{jk,pp}\log(\widetilde{P}_{j,it})\log(\widetilde{P}_{k,it}) && \text{(I)}\\
&+\sum_{j=2}^{4}\sum_{\ell=1}^{5}\beta_{j\ell,py}\log(\widetilde{P}_{j,it})\log(Y_{\ell,it}) + \sum_{\ell=1}^{5}\beta_{\ell,y}\log(Y_{\ell,it}) && \text{(II)}\\
&+(1/2)\sum_{\ell=1}^{5}\sum_{m=1}^{5}\beta_{\ell m,yy}\log(Y_{\ell,it})\log(Y_{m,it}) + \sum_{\ell=1}^{5}\beta_{\ell,ty}t\log(Y_{\ell,it}) && \text{(III)}\\
&+\sum_{\ell=1}^{5}\beta_{\ell,tty}t^2\log(Y_{\ell,it}) + \sum_{t}\beta_t d_t + \eta_{it}, && \text{(IV)}
\end{aligned}$$

where t denotes a time trend, d_t a dummy for year t and η_{it} a mean-zero error term orthogonal to the covariates. Equation (I) is a long-run cost function because input price changes are instantaneously and fully incorporated in total costs. The corresponding long-run optimal cost shares for $j = 2, \ldots, 4$ are

$$\begin{aligned}
w^*_{j,it} \;=\;& \partial\log(\widetilde{C}_{it})/\partial\log(\widetilde{P}_{j,it}) = \beta_{j,p} + \sum_{k=2}^{4}\beta_{jk,pp}\log(\widetilde{P}_{k,it}) + \sum_{\ell=1}^{5}\beta_{j\ell,py}\log(Y_{\ell,it}); && \text{(V)}\\
w^*_{1,it} \;=\;& 1 - w^*_{2,it} - w^*_{3,it} - w^*_{4,it}.
\end{aligned}$$

The equality between the cost shares and the cost elasticities with respect to input prices follows from Shephard's lemma. To capture the dynamics between long-run optimal cost shares ($w^*_{j,it}$) and short-run actual shares ($w_{j,it}$), Urga and Walters (2003) assume the following short-run cost function:

$$\begin{aligned}
\log(C_{it}) \;=\;& m\log(C^*_{it}) + (1-m)\log(C^*_{it-1}) + (1-m)\sum_{j=2}^{4}\Big(w_{j,it-1}\log(P_{j,it}) - w^*_{j,it-1}\log(P_{j,it-1})\Big)\\
&+ \sum_{j=1}^{4}\sum_{k=2}^{4} b_{jk}(w^*_{k,it-1} - w_{k,it-1})\log(P_{j,it}), && \text{(VI)}
\end{aligned}$$

where $\log(C^*_{it})$ denotes the linear predictor of $\log(C_{it})$ based on the model of Equation (I). As explained by Urga and Walters (2003), the short-run cost function admits the interpretation of a partially generalized error-correction mechanism of Anderson and Blundell (1982, 1983, 1984). The parameter $m > 0$ controls the dynamics and is referred to as the control or adjustment parameter. The short-run cost function of Equation (VI) implies the following short-run cost shares for $j = 2, \dots, 4$:

$$w_{j,it} = mw^*_{j,it} + (1-m)w_{j,it-1} + \sum_{k=2}^{4} b_{jk}(w^*_{k,it-1} - w_{k,it-1}). \tag{VII}$$

To ensure identification of the short-run cost function, one cost-share equation is left out in Equation (VI). Moreover, identification also requires joint estimation of the short-run cost function and three out of four short-run factor share equations, using ML or the equivalent Zellner iterated SUR estimator (Urga and Walters, 2003). Moreover, we impose the normalization $\sum_{k=1}^{4} b_{jk} = 0$. To estimate the short-run cost function, long-run costs and cost shares are replaced by their predicted counterparts based on OLS estimation of Equation (I), whereas the short-run costs and cost shares are replaced by the observed ones. The resulting estimates are invariant to the omitted cost-share equation.

2.3. Substitution elasticities

The long-run own-price and cross-price elasticities of substitution write as

$$E^{LR}_{jj,it} = (\gamma_{jj} + (w^*_{j,it})^2 - w^*_{j,it})/w^*_{j,it}, \quad E^{LR}_{jk,it} = (\gamma_{jk} + w^*_{j,it}w^*_{k,it})/w^*_{j,it}, \tag{VIII}$$

while short-run own-price and cross-price elasticities involve the control parameter m and equal

$$E^{SR}_{jj,it} = m\gamma_{jj}/w^*_{j,it} + w^*_{j,it} - 1, \quad E^{SR}_{jk,it} = m\gamma_{jk}/w^*_{j,it} + w^*_{k,it}. \tag{IX}$$

2.4. Extensions

It is straightforward to extend the dynamic generalized translog demand system to a more flexible translog specification, such as the flexible Fourier model. This modification will only affect the functional form of the underlying long-run cost function, whereas the short-run cost function and the partially generalized error-correction model for the short-run cost shares will have the same form as above.

2.5. Estimation results

Table 3 displays the estimation results for the DTD system.

3. Robustness checks

This appendix discusses the outcomes of several robustness checks.

3.1. *Unbalanced samples*

Table 2 displays the estimated substitution elasticities based on the two subsamples. We observe only marginal differences between these estimates and those based on the balanced samples. From these results it is clear that survivorship bias is not an issue in this research.

3.2. *Morishima elasticities*

Frondel (2011) refers to the cross-price elasticity as a one-price-one-factor elasticity of substitution, which provides a measure of absolute substitutability. In contrast to the cross-price elasticity, the Morishima elasticity is a two-factor-one-price elasticity of substitution and provides a measure of relative substitutability (Frondel, 2011) . Furthermore, Blackorby and Russell (1989) show that the Morishima elasticity is directly linked to the change in relative cost shares in response to a change in input prices:

$$\frac{\partial \log(w_{j,it}/w_{k,it})}{\partial \log(P_{k,it})} = M_{jk} - 1. \tag{X}$$

The Morishima elasticity of substitution is an appropriate measure for assessing both quantitatively and qualitatively the effects of changes in relative prices on relative factor shares in the presence of more than two input factors. Our main analysis focuses on the own-price and cross-price elasticities of substitution instead of the Morishima elasticities though. As shown by Frondel (2004, 2011), the former elasticities have a more appealing interpretation in terms of the change in input prices on input demand *levels* instead of input demand *ratios* (Frondel, 2004, 2011).

As a robustness check, we have redone the entire analysis using Morishima elasticities, thereby focusing on relative instead of absolute substitutability of input factors. The Morishima elasticities also exhibit a significant drop after the onset of the crisis. These results are available upon request.

3.3. *Substitution elasticities that depend on time and bank size*

In Section 2 of the main text, we 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 estimated and extended version of the DLD model that captures both time-varying and bank size-dependent substitution elasticities and adjustment coefficients. We use the natural logarithm of total assets ('log_bank_size') as a measure of bank size and specify, for bank i in year t:

$$\begin{aligned}
\beta^*_{jk,it} &= \beta^{0*}_{jk} + \beta^{c*}_{jk}\text{crisis_dum} + \beta^{s*}_{jk}\text{log_bank_size}_{it} + \beta^{sc*}_{jk}\text{log_bank_size}_{it} \times \text{crisis_dum}; && \text{(XI)} \\
\gamma_{j\ell,it} &= \gamma^0_{j\ell} + \gamma^c_{j\ell}\text{crisis_dum} + \gamma^s_{j\ell}\text{log_bank_size}_{it} + \gamma^{sc}_{j\ell}\text{log_bank_size}_{it} \times \text{crisis_dum}; && \text{(XII)} \\
\lambda_{it} &= \lambda^0 + \lambda^c\text{crisis_dum} + \lambda^s\text{log_bank_size}_{it} + \lambda^{sc}\text{log_bank_size}_{it} \times \text{crisis_dum}. && \text{(XIII)}
\end{aligned}$$

We notice that the extended DLD model satisfies symmetry and linear homogeneity. This is due to the fact that the model coefficients are functions of explanatory variables that depend on neither i (the input price that changes) nor j (the input factor that responds). Furthermore, the resulting elasticities satisfy the *Le Chatelier* principle. We estimate the extended DLD system in a similar fashion as we estimate the standard DLD system.

To estimate substitution elasticities based on the extended DLD model, we first choose a fixed bank size and a binary value for the crisis dummy. Subsequently, we calculate the elasticity parameters according to Equations (XI) and (XIII), and substitute them into Equations (5) and (6) of the main text. This approach allows us to investigate the impact of bank size on the elasticity drop after the onset of the crisis. Furthermore, the estimate of λ^{sc} can be used to test whether bank size affected the change in lag time after the onset of the crisis.

Because the coefficients of the interaction variables involving bank size do not turn out significant, the role of bank size is only minor. This is confirmed when we calculate the associated substitution elasticities for banks with total assets equal to the 10% sample quantile ('small banks') and for banks with total assets equal to the 90% sample quantile ('large banks').

3.4. *Alternative estimator*

To account for bank-specific fixed effects, it seems natural to transform each share equation in Equation (3) of the main text into first differences. Subsequently, we could apply system OLS or SUR-GLS to the resulting share-equation system (Considine and Mount, 1984; Considine, 1990). However, the resulting estimator will be biased due to dynamic panel effects. The Nickell bias is caused by the term $\log(Q_{j,it-1}/Q_{4,it-1}) = \log(w_{j,it-1}/w_{4,it-1}) - \log(P_{j,it-1}/P_{4,it-1})$. That is, each share equation is a dynamic panel model, containing a lagged share ratio. Hence, SUR-GLS or system OLS applied to the first-differenced DLD system will be biased (e.g., Anderson and Hsiao, 1981). The same holds for the system transformed by means of the within transformation and the system including RE instead of FE (Cameron and Trivedi, 2005). Nevertheless, we could apply system panel IV estimation to the first-differenced share-equation system, with $\log(Q_{j,it-2}/Q_{4,it-2})$ as an instrument in equation $j = 1, 2, 3$ (Anderson and Hsiao, 1981). We could also explore GMM estimation with instruments of the Arellano-Bond type.

However, we are then left with the issue of *invariance* of the chosen estimator to the choice of the numéraire in the logit demand system. Maximum likelihood (ML) estimation is often associated with invariance because of 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. The present setting is more complex though. First, it is not straightforward how to extend the ML approach of Hsiao et al. (2002) for dynamic panel models to the present framework of systems of dynamic panel equations. Second, even if we were be able to use this form of ML estimation, it is not clear whether this would result in an invariant estimator. For example, the structural autoregressive parameters of the model errors in Equation (3) of the main text would have to satisfy certain restrictions to achieve invariance (Chavas and Segerson, 1986). In sum, it is not clear whether and under what conditions an invariant estimator exists in the present case. Although IV/GMM estimation is a convenient choice in the presence of dynamic panel effects, the associated estimators are not invariant with respect to the choice of numéraire due to the presence of cross-equation restrictions. The same holds for GMM-extensions such as iterative GMM and CUE (something we have investigated explicitly).

As noted by Berndt and Savin (1975, p. 946), *"lack of invariance leaves open the possibility that the investigator may choose to report only those estimates and test results which most closely correspond with his personal preferences"*. We have therefore assessed the robustness of the results based on the system panel IV estimator that arbitrarily takes the fourth input as the numéraire. The choice of the numéraire turns out to matter in a quantitative way, confirming the point made by (Barten, 1969). These results are available upon request.

The invariance issue is our main motivation for resorting to the invariant SUR-GLS estimator in the main text. The estimation results show that 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. This finding suggests indeed that there is limited cost-share heterogeneity across banks. Intuitively, cost shares indeed seem less heterogeneous than cost levels.

By accounting for cross-equation correlation only, the SUR-GLS estimator is inefficient. Given our large sample size, this is not a problem. We obtain consistent confidence intervals by making use of the bootstrap, thus accounting for cross-sectional correlation, heteroskedasticity and autocorrelation.

Finally, we notice that the system panel IV and the SUR-GLS estimators quantitatively agree on our most important results. Both estimators confirm that virtually all substitution elasticity have dropped after the onset of the crisis but that the substitutability of labor for physical capital has remained relatively high.

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Table 1: Definition of variables

Variable	**Series**
consumer loans	RCFD1975
real estate loans	RCFD1410
business and other loans	RCFD1400-RCFD1410-RCFD1975
off-balance sheet items	RIAD4079-RIAD4080
securities	RCFD1754+RCFD1773
purchased funds	RCON2604+RCFD2800+RCFD3548+RCFD3200+ RCFD3190+RCFD2200-RCON2200
core deposits	RCON2200-RCON2604
# of full-time equivalent employees	RIAD4150
physical capital	RCFD2145
expenditures on purchased funds (interest)	RIAD4172+RIAD4180+RIADA517+ RIAD4185+RIAD4200
expenditures on core deposits (interest)	RIAD4170-RIADA517- RIAD4172
expenditures on labor services (salaries)	RIAD4135
expenditures on physical capital	RIAD4217
price of purchased funds	(expenditures on purchased funds)/(purchased funds)
core deposit rate	(expenditures on core deposits)/(core deposits)
wage rate	(expenditures on labor services)/(# of full-time equivalent employees)
price of physical capital	(expenditures on physical capital)/(physical capital)
total assets	RCFD2170
BHC	RSSD9364
bank index	RSSD9050
time index	RSSD9999

Notes: This table explains how the variables in this study have been calculated from the data available in the Call Reports. Throughout, level variables are deflated using the Consumer Price Index for All Urban Consumers.

Table 2: Estimated substitution elasticities based on the DLD system (unbalanced samples)

	SHORT-RUN				*LONG-RUN*			
	2000 – 2008							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.3908**	**0.1530**	**0.2009**	**0.0368**	**-2.0416**	**0.7995**	**1.0497**	**0.1924**
L	-0.4032	0.1427	0.1932	0.0339	-2.1224	0.7412	1.0048	0.1765
U	-0.3772	0.1626	0.2090	0.0397	-1.9621	0.8527	1.0987	0.2091
CD	**0.0746**	**-0.0792**	**-0.0048**	**0.0094**	**0.3897**	**-0.4136**	**-0.0252**	**0.0491**
L	0.0696	-0.0844	-0.0076	0.0080	0.3612	-0.4408	-0.0403	0.0420
U	0.0793	-0.0736	-0.0020	0.0108	0.4156	-0.3838	-0.0106	0.0560
LS	**0.0881**	**-0.0043**	**-0.1159**	**0.0322**	**0.4600**	**-0.0226**	**-0.6055**	**0.1681**
L	0.0847	-0.0069	-0.1206	0.0306	0.4403	-0.0363	-0.6274	0.1613
U	0.0916	-0.0018	-0.1121	0.0337	0.4815	-0.0096	-0.5854	0.1748
PC	**0.0641**	**0.0336**	**0.1278**	**-0.2254**	**0.3347**	**0.1754**	**0.6675**	**-1.1775**
L	0.0589	0.0284	0.1216	-0.2316	0.3070	0.1498	0.6405	-1.2006
U	0.0691	0.0386	0.1337	-0.2189	0.3638	0.1998	0.6940	-1.1575
	2009 – 2013							
	PF	**CD**	**LS**	**PC**	**PF**	**CD**	**LS**	**PC**
PF	**-0.2131**	**0.0708**	**0.1256**	**0.0167**	**-1.5531**	**0.5159**	**0.9153**	**0.1219**
L	-0.2247	0.0640	0.1163	0.0125	-1.6759	0.4630	0.8442	0.0906
U	-0.2015	0.0775	0.1352	0.0210	-1.4512	0.5765	0.9990	0.1543
CD	**0.0475**	**-0.0656**	**0.0053**	**0.0128**	**0.3459**	**-0.4778**	**0.0387**	**0.0932**
L	0.0429	-0.0705	0.0007	0.0102	0.3105	-0.5210	0.0055	0.0758
U	0.0519	-0.0606	0.0098	0.0155	0.3865	-0.4408	0.0715	0.1117
LS	**0.0279**	**0.0018**	**-0.0580**	**0.0283**	**0.2037**	**0.0129**	**-0.4230**	**0.2064**
L	0.0259	0.0002	-0.0612	0.0266	0.1879	0.0018	-0.4447	0.1980
U	0.0301	0.0032	-0.0548	0.0301	0.2223	0.0237	-0.4028	0.2149
PC	**0.0159**	**0.0181**	**0.1211**	**-0.1552**	**0.1160**	**0.1322**	**0.8830**	**-1.1312**
L	0.0119	0.0145	0.1136	-0.1634	0.0862	0.1076	0.8470	-1.1620
U	0.0200	0.0220	0.1286	-0.1466	0.1468	0.1586	0.9194	-1.0997

Notes: This table displays point estimates and 95% confidence intervals for the SR and LR own-price and cross-price elasticities based on the dynamic version of the share equation 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 PPW 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. All elasticities have been estimated using unbalanced versions of the pre-crisis sample (2000 – 2007) and the (post-)crisis sample (2008 – 2013).

Table 3: Estimation results for the DTD system

	2000 – 2008			**2009 – 2010**		
	p.e.	**2.5%**	**97.5%**	**p.e.**	**2.5%**	**97.5%**
m	0.7784	0.7245	0.8032	0.7446	0.6463	0.7736
b_{11}	-1.0328	-1.1002	-0.9239	-1.1566	-1.3373	-0.8611
b_{12}	1.0222	0.9728	1.0846	0.8989	0.7478	1.0122
b_{13}	0.3649	0.2812	0.4014	0.3490	0.2751	0.3733
b_{14}	-0.3544	-0.4023	-0.3158	-0.0912	-0.1875	-0.0247
b_{21}	0.5754	0.5228	0.5988	0.6485	0.5369	0.7046
b_{22}	-0.6725	-0.6982	-0.6229	-0.6275	-0.6674	-0.5355
b_{23}	-0.0076	-0.0162	0.0049	-0.0740	-0.0887	-0.0643
b_{24}	0.1046	0.0959	0.1157	0.0530	0.0267	0.0849
b_{31}	0.0458	-0.0157	0.1128	0.0693	-0.0521	0.2332
b_{32}	-0.0002	-0.0315	0.0365	-0.1053	-0.1976	-0.0470
b_{34}	-0.4202	-0.4511	-0.3976	-0.3714	-0.4248	-0.3293
b_{33}	0.3746	0.3378	0.4059	0.4075	0.3647	0.4546
b_{41}	0.6483	0.5688	0.7071	0.4160	0.2313	0.5056
b_{42}	-0.0110	-0.0347	0.0128	0.1983	0.1396	0.2857
b_{43}	-0.2674	-0.3013	-0.2420	-0.1050	-0.1517	-0.0676
b_{44}	-0.3699	-0.4120	-0.2953	-0.5092	-0.5500	-0.3867
system R^2	0.93			0.96		

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) of Equation (VI). This equation has been estimated jointly with the cost-share Equations (V) (where we left out the first cost-share equation), using Zellner's iterated SUR estimator (which is equivalent to ML under normality). The coefficients b_{11}, b_{21}, b_{31} and b_{41} have been estimated indirectly using the normalization constraint $b_{k1} = -\sum_{j=2}^{4} b_{kj}$. The confidence intervals are based on the PPW bootstrap with $B = 1,000$ bootstrap runs and robust for heteroskedasticity, autocorrelation and contemporaneous correlation between the error terms of the model equations. The DTD system has been estimated using the subsamples 2000 – 2007 and 2008 – 2013. The estimation results for the long-run cost translog function of Equation (I) are not reported to save space.