Journal of Banking & Finance 69 (2016) S10–S24

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

How capital regulation and other factors drive the role of shadow banking in funding short-term business credit ☆

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ARTICLE INFO

Article history:
Received 10 October 2014
Accepted 22 June 2015
Available online 11 July 2015

JEL classification:
E44
E50
N12

Keywords:
Shadow banking
Regulation
Financial frictions
Credit rationing

ABSTRACT

This paper empirically analyzes how capital regulation, risk, and other factors altered the relative use of shadow banking-funded, short-term business debt since the early 1960s. Results indicate that the share was affected over the long run not only by changing information and reserve requirement costs, but also by shifts in relative regulation of bank versus nonbank credit sources—such as Basel I in 1990 and reregulation in 2010. In the short-run, the shadow bank share rose when deposit interest rate ceilings were binding on traditional banks, the economic outlook improved, or risk premia declined, and fell when event risks arose.

1. Introduction

The relative importance of the "shadow banking system" generally increased in the decades preceding the 2007–09 financial crisis in the U.S. and subsided following the crisis amid efforts to reform the financial system. For example, the share of short-term business credit of nonfinancial corporations funded by securities markets—e.g., nonbank loans funded with uninsured debt, securitized bank loans, and commercial paper directly issued by nonfinancial corporations—has roughly doubled since the late 1960s (Fig. 1). Netting out commercial paper, there have been large shifts in the share funded through the shadow system.[1]

The existing literature offers a number of potential factors that drove these developments—ranging from the long-run effects of regulatory arbitrage and financial innovation to short-run cyclical and financial market shocks—but there is little empirical evidence that assesses such factors jointly and that provides perspective on their actual roles. Addressing this gap in the literature, this study tracks and synthesizes these factors into a cohesive empirical framework that provides estimates about how various factors drove both the long-run evolution of and the short-run variation in shadow banking's relative importance in funding short-term nonfinancial corporations over the past half-century.

This is particularly relevant to understanding the role of shadow banking in the global financial crisis and its aftermath for several reasons. First, experience reflects that commercial paper and debt issued by nonbank financial firms are both vulnerable to financial market shocks and can be pro-cyclical, as reflected in the sharp post-2007 drop in shadow bank lending and as emphasized in recent papers by Adrian and Shin (2009a, 2009b, 2010), Geanakoplos (2010), Gennaioli et al. (2013), and Gorton and Metrick (2012), *inter alia*. Second, the size of the shadow system

☆ I especially thank Stijn Claessens for his discussant comments on an earlier version presented at Yale, and I also thank two anonymous referees, Dirk Bezemer, Eric Beinhocker, Doyne Farmer, Gary Gorton, John Muellbauer, Elizabeth Organ, and Michael Weiss for comments on drafts or presentations of the paper. I also thank J.B. Cooke for excellent research assistance. For their comments on earlier versions of this research, I thank participants in presentations and seminars at the 16th Annual International Banking Conference co-sponsored by the Federal Reserve Bank of Chicago and the International Monetary Fund, the inaugural 2014 conference of Yale School of Management's Program on Financial Stability, the 2014 FEBS Symposium in Surrey, Hong Kong Institute for Monetary Research, and Oxford University. The views expressed are those of the author and are not necessarily those of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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[1] The security-funded share plotted in Fig. 1 internalizes substitution between commercial paper directly issued by nonfinancial firms and credit to nonfinancial corporations.

http://dx.doi.org/10.1016/j.jbankfin.2015.06.016
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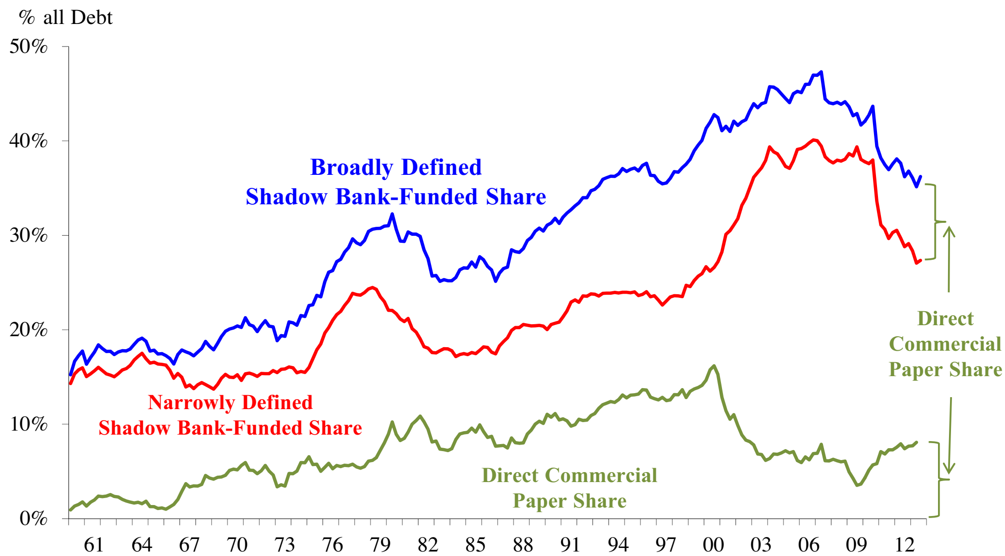

Fig. 1. The relative importance of the shadow banking system as tracked by the security-funded share of short-run nonfinancial business credit.

can affect the magnitude of such effects (e.g., through fire-sale effects as in Luck and Schempp, 2014). For these reasons, the size of the shadow banking system and its reaction to liquidity shocks make the real economy vulnerable to credit shortages stemming from flights to quality. Furthermore, these effects may not be fully offset by banks, especially if correlated loan losses impair the capital adequacy of bank and nonbank financial firms, as occurred in the 2008 crisis. By quantifying the various factors affecting the shadow bank share of short-term nonfinancial business credit, the financial architecture model developed here can help inform not only short-run policy responses to financial crises, but also the long-run design of financial systems that balance the gains from sound financial innovation with the need for some financial stability.

To establish these findings, this study is organized as follows. Section 2 provides a brief literature review of how shadow banking has been defined elsewhere and of the factors that have affected the relative use of shadow banks as a source of short-run business finance since the early 1960s. Building off these insights, Section 3 presents an estimable, empirical specification for modeling the relative reliance of nonfinancial firms on shadow-funded debt. Section 4 reviews the main empirical results using quarterly data since the early 1960s, and Section 5 provides some additional robustness checks. Findings are interpreted in Section 6, which draws parallels with the experience of the 1930s.

2. Literature review: what is shadow banking and what drives it?

The literature touches on two major aspects of shadow banking relevant for this study's empirical assessment of what has driven nonfinancial businesses' use of the shadow banking system as a source of short-term credit. The first is defining shadow banking and the second concerns the factors driving its use over time?

2.1. Defining shadow banking

Attempts to define and measure shadow banking take several approaches. Of these, the definition used in this paper is close in spirit to the seminal work of Pozsar et al. (2010, 2012) in three key respects. First, within the segment of nonfinancial corporate debt, the definition is similar to Pozsar et al. (2010, 2012, pp. 7–8) who combine the liabilities in the flow of funds related to securitization with short-term money instruments not backstopped by deposit insurance (e.g., commercial paper) in gross and net calculations. Second, shadow bank credit lacked the access to public backstops (e.g., deposit insurance or Federal Reserve liquidity facilities) except when during the recent crisis, official liquidity facilities and credit guarantees replaced private sector guarantees, to paraphrase Pozsar et al. (2010, 2012, p. 2).[2] Third, the definition used here combines debt primarily funded through two of the three broad shadow subcategories of Pozsar et al. (2010, 2012)—the internal and external shadow bank subsystems. However, it effectively omits the government-sponsored shadow bank subsystem by excluding debt secured by real estate, an aspect of shadow banking not covered in the present study.

A slightly different approach is taken by the Financial Stability Board ("FSB," 2012, p. 3), which defines shadow banking as, "credit intermediation involving entities and activities outside the regular banking system". The FSB later clarifies this as inclusive of securitization and nonbank lenders. The definition was subsequently further modified to include "entities and activities *fully or partially* outside the regular banking system, *or non-bank credit intermediation in short*," (italics indicate modifications, FSB, 2014, p. 4). The variable tracking shadow banking in this paper has some similarities with this definition, but is narrower because it focuses on sources of short-term corporate debt, does not include off-balance sheet products that have not been tracked over time, and is less focused on the asset-transformation activities that shadow banks use to raise funds.

In general, for practical estimation purposes, the current study more narrowly focuses on one dimension of nonfinancial corporate short-term debt, whereas in the broader views of shadow banking—exemplified by the FSB (2012) and Pozsar et al. (2010, 2012)—shadow banks serve key roles on both the asset and liability sides of the overall financial sector balance sheet. For example, Claessens et al. (2012) discuss in detail how shadow banks address several unmet financial needs, noting that the liabilities that shadow banks create help address the need for collateral in financial markets and that shadow banks similarly help address some credit demands unmet by commercial banks. Another aspect of shadow banking is that shadow and more conventional bank activities are often intertwined (see Claessens et al. (2012) and Jackson (2013)), which raises some limitations and qualifications for

[2] An alternative definition of Claessens and Ratnovski (2014) proposes defining shadow banking as, "all financial activities, except traditional banking, which require a private or public backstop to operate".

tracking shadow banking by looking at a simple disaggregation of credit or liabilities by financial intermediary type.

2.2. What drives shadow banking?

The existing literature on nonbank finance has mentioned several factors behind the rise of shadow banking over the past decades. Some older studies emphasize how reserve and other regulatory requirements encourage the use of alternatives to bank loans (e.g., Kanatas and Greenbaum (1982), Bernanke and Lown (1991), Berger and Udell (1994) and Duca (1992)) and the rise of securitization going back to at least Pennacchi (1988). Also contributing to the long-run rise are changes in information costs, which though mentioned in some studies (e.g., Edwards and Mishkin, 1995; Ratnovski, 2013), have been rarely empirically assessed.

In the short-run, credit can shift from risky to safer borrowers if default risk rises or the cost of funds rises, owing to higher liquidity risk premiums (e.g., Bernanke and Blinder, 1988; Bernanke and Gertler, 1989; Bernanke et al., 1996; Duca, 2013b; Jaffee and Russell, 1976; Keeton, 1979; Lang and Nakamura, 1995; Stiglitz and Weiss, 1981). Newer studies find that movements in the spreads between investment grade corporate and Treasury interest rates mainly reflect swings in liquidity risk and risk aversion (Friewald et al., 2012).

More recent literature has emphasized the susceptibility of financial firms and the financial system to liquidity risk (e.g., Adrian and Shin, 2009a,b, 2010; Gennaioli et al. (2013)). Consistent with these theories, the experience of the Great Depression indicates that security-funded sources of external finance, such as commercial paper, are vulnerable to the jumps in risk premia typical of financial crises (Duca, 2013b). Indeed, real commercial paper outstanding fell 85% between July 1930 and May 1933 when spreads between corporate and Treasury bond yields jumped, accompanied by a rise in the relative and absolute use of bankers acceptances (BAs), a more liquid and collateralized money market instrument than un-backed commercial paper.[3]

Recent experience suggests that jumps in risk premiums can be countered by central bank asset purchases that cushion the supply of security-funded credit to top-rated borrowers (see Anderson and Gascon, 2009; Duca, 2013a; Duygan-Bump et al., 2013 on the Fed's commercial paper facility, and Goodhart, 1987 on the need for a broad lender of last resort). For example, real commercial paper fell 74% during the 25 months between July 1930 and August 1932, but by a less dramatic 44% between July 2007 and August 2009. The smaller decline in the recent Great Recession partly reflects that in contrast to the 1930s, the Federal Reserve purchased commercial paper and residential mortgage-backed securities to limit surges in risk premia. Additionally, there was a relatively stronger macroeconomic policy response to the Great Recession.

Despite the limited literature on policy actions intended to counter the Great Recession, there has been little econometric analysis of what factors contributed to shadow banking's rise before the recent crisis and its more recent partial retrenchment, likely reflecting several challenges. One is how to measure the shadow banking system, whose earlier rise was bolstered mainly by increased securitization of residential mortgages (see Pozsar et al., 2010, 2012) and a greater role of shadow banks in funding business. To avoid or limit the difficulties with blending household and business borrowing, as well as credits of mixed duration, this study focuses on the relative importance of shadow banks in funding short-run business credit. Using a half-century of data, the roles of several potential factors—not just the latest fad—are assessed. The sample is extensive enough to disentangle short- from long-term effects. The time series analysis, by not being limited to the Great Moderation era, draws from experience spanning different regulatory regimes, which may provide more perspective concerning recent attempts at financial reform.

This study assesses how the relative importance of shadow banking is affected by short- and long-run factors stemming from regulatory burdens and information costs, drawing on insights from Kashyap et al. (1993) on the role of commercial paper in short-run business finance and Oliner and Rudebusch (1996) regarding broad-based rather than narrow-based (bank) views of the credit channel of monetary policy. The models use data from the Federal Reserve's Financial Accounts, covering a broad range of credit funded with commercial paper and other market debt. The relative use of credit funded by commercial paper (commercial paper and nonbank loans funded by securities issued by finance companies and asset-backed securities (ABS) lenders) versus bank loans reflects the advantages of avoiding bank regulations (e.g., reserve and capital requirements, see Kanatas and Greenbaum, 1982) relative to the advantages of banks having information and transactions cost advantages in lending and funding sources that are less exposed to the effects of shifting risk premia in securities markets.

For these reasons, movements in the relative use of security- or shadow-funded credit could reflect the combination of influences stressed in (1) older literature that emphasizes how reserve and other regulatory requirements encourage the use of alternatives to bank loans (e.g., Kanatas and Greenbaum, 1982), (2) the asymmetric information literature that models the composition of lending (e.g., Diamond, 1991; Jaffee and Modigliani, 1969; Kashyap et al., 1993), (3) the theoretical and empirical literature on the securitization of bank loans (e.g., Pennacchi, 1988), and (4) newer literature examining the role in the recent financial crisis of procyclical liquidity premia and leverage (e.g., Adrian and Shin (2009a, 2009b, 2010), Geanakoplos (2010), Gorton and Metrick (2012)). With regard to the fourth strand of literature, lenders' ability to fund loans with debt—whether through securitization by banks or by ABS entities—depends critically on how much collateral investors demand or equivalently how much leverage markets allow lenders. In their model of lending funded without insured deposits, Shleifer and Vishny (2010) theoretically show that such lending can dry up if investors demand higher risk premia, a point that Adrian and Shin (2009a,b) empirically demonstrate and that Adrian and Shin (2010) analyze in a more market-oriented context.

2.3. How the current study fits into the literature

The current study focuses on assessing the factors driving one aspect of shadow banking: namely, the relative role of shadow banking in supplying short- and intermediate term business credit over time. This narrows the scope of the empirical analysis to one role of shadow banking (supplying credit) for one segment (nonfinancial corporations) in one maturity range (short- and medium-term). Analysis of other aspects of shadow banking is left to future research (e.g., the changing role of shadow banks in supplying new types of liabilities to meet a growing need for collateral). The availability of consistently defined time series data prevents testing more detailed hypotheses (e.g., how borrowers' credit needs are met with soft versus hard information—see Ratnovski, 2013). Nevertheless, some roles played by commercial banks in shadow banking are addressed—e.g., treating securitized commercial and industrial (C&I) loans as a form of shadow credit.

[3] BAs are time drafts drawn on banks to finance the shipment or storage of goods. Banks guarantee payment to BA investors, making BAs tradable as investors know more about banks than goods buyers. The latter receive credit to pay sellers from banks that fund credits by selling BAs. Goods collateralize BAs for banks unlike the unbacked commercial paper of the 1930s and more recent asset-based securities (ABS) paper that is backed by paper assets of volatile market value.

3. Model specification and data

3.1. Modeling the relative use of security market-funded versus deposit-funded loans

For several reasons, this paper empirically models the shadow bank share of short-term debt for nonfinancial corporations—that is, funded directly from commercial paper and indirectly from non-bank financial intermediaries. First, much commercial paper is held by money market mutual funds, a type of shadow bank whose importance grew out of efforts to circumvent the burden of bank regulation (regulatory arbitrage). Second, the shadow bank share internalizes substitution between commercial paper directly issued by nonfinancial corporations and credit intermediated by nonbank financial intermediaries (Fig. 1). This substitution became pronounced following the rise and fall of structured finance. Shadow banking system use increased following the passage of the Commodity Futures Modernization Act (CFMA) of 1999—which made many derivatives contracts outside of currency and interest-rate swaps enforceable or legally certain (Roe, 2011; Stout, 2008), partly by giving derivatives priority in bankruptcy (Bolton and Oehmke, 2011, forthcoming; Roe, 2011; Stout, 2012, p. 1208, footnote 123). Shadow banking prominence later plunged after passage in 2010 of the Dodd-Frank (DFA) financial reform act, which partially leveled the regulatory playing field between commercial and shadow banking. Third, modeling the relative use of shadow bank funding is hampered by the unavailability of complete data on various funding sources, particularly in the financial sector and in the unincorporated business sector. For this reason, modeling the structure of external finance for nonfinancial corporations is more feasible. Fourth, another challenge is controlling for the substitutability of different maturities of debt and between debt and equity financing.

To limit such distortions and measurement error issues, this paper focuses on modeling the security market-funded share of short-term nonfinancial corporate debt, which is also referred to as the shadow bank share. By focusing on modeling a shadow bank share rather than the level of shadow bank credit, the paper largely abstracts from demand factors that plausibly affect the numerator and denominator of a market share variable in the same direction. The model focuses on short-run debt, which tends to reflect working capital needs, rather than long-run investment requirements. Thus, there is much less need to model volatile business fixed investment, complications from modeling the drawn-out resolution of bad real estate loans,[4] and thorny changes in the mix of debt and equity. Partly to limit any impact on model estimates from substitution between short- and long-term debt, the models also include the slope of the Treasury yield curve. While the analysis does not measure the comparative vulnerability of the financial system to funding from security markets versus funding from insured deposits, it assesses the vulnerability of short-run nonfinancial corporate debt to nonbank sources. In this sense, there are parallels to the shadow bank definition of Claessens and Ratnovski (2014) insofar as the study distinguishes between credit funded by sources with a federal government backstop from those funded by shadow sources that either have a nonbank financial intermediary backstop or have limited security market backstops in the form of collateral, such as asset-backed commercial paper.[5] One difference with the FSB's (2014, bottom p. 5) definition[6] is that the definition used here includes security-market funded short-run debt (of nonfinancial corporations) that banks or non-financial intermediaries may hold. Although the noncorporate and financial corporate sectors are not modeled, it is useful to note that the nonfinancial corporate sector produces the vast bulk of U.S. GDP. Together, the aforementioned considerations indicate that modeling the short-run credit needs of nonfinancial corporations is both relevant and feasible.

An error-correction framework is used to estimate long-run (equilibrium) and short-run movements in the shadow share. This approach is well-suited for this purpose because unlike traditional econometric techniques, it allows one to model nonstationary variables like the shadow share as a function of the other variables, provided that the variables are cointegrated—that is the deviation between actual and equilibrium levels are themselves stationary. This approach also improves upon the ability to track short-run movements which should tend to narrow (correct) the gap between the actual and equilibrium levels, proxied by the prior period's gap (or error).

The long-run relative use of shadow or security market-funded credit (*SHADOW*) can be modeled as a function of nonstationary (*X* vector) and stationary (*Z* vector) regulatory and risk variables reflecting the factors mentioned above. Short-run changes in *SHADOW* can be modeled as a function of an error-correction term ($EC \equiv$ actual minus equilibrium log-levels of *SHADOW*), short-run variables, and first-differences of any nonstationary *X* components:

$$\begin{aligned}
&\log(SHADOW) = \lambda_0 + \lambda_1 \log(X) + \lambda_2(Z)\\
&\Delta \log(SHADOW)_t = \alpha_0 + \alpha_1 \log(EC)_{t-1} + \beta_i \Delta \log(SHADOW)_{t-i}\\
&\qquad\qquad + \theta_i \Delta \log(X)_{t-i} + \delta Z_t\\
&EC \equiv \log(SHADOW) - [\lambda_0 + \lambda_1 \log(X)]
\end{aligned} \tag{1}$$

This approach can be implemented with enough time series data. The only consistent, long-running time series source of data to track *SHADOW* into the recent period is the Federal Reserve Board's quarterly Financial Accounts (formerly, Flow of Funds). Higher frequency monthly data on commercial paper that span direct and asset-back commercial paper suffer from sample breaks and are consistently available only since 2001, making it difficult to identify long-run relationships because short-run trends may dominate sample periods of limited length.

3.2. Data and variables

Most of the determinants of the shadow share reflect either information costs or regulatory arbitrage. For information costs, there are a handful of possible time series measures, whereas the regulatory arbitrage variables reflect the influence of several elements, most notably reserve requirement taxes, deposit regulations, and the relative burden of capital requirements on banks as opposed to nonbank financial intermediaries and securities markets. In addition, short-run financial shocks are also be tracked. Following a description of how shadow banking is observed, the variables tracking its determinants are discussed in the order mentioned above.

3.2.1. Relative use of shadow bank or security market funded credit

The relative use of securities-funded credit is analyzed using the variable *SHADOW*, which is a ratio based on quarterly Financial

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[4] Note that this also omits a dominant piece of the broader shadow banking sector definition of Pozsar et al.'s (2010, 2012), which encompasses real estate assets funded by the government sponsored enterprises, private-label residential mortgage-backed securities, and commercial mortgage-backed securities.

[5] The back-up lines of bank credit that back commercial paper do not prevent paper from becoming illiquid during crises. In an operational sense, the value of an indirect bank backstop does not fully secure funding in this market.

[6] "Non-bank financial intermediation is measured by total financial assets held by Other Financial Intermediaries (OFIs), which include all non-bank financial intermediaries with the exception of insurance companies, pension funds and public financial institutions. This broad measure is referred to as the Monitoring Universe of Non-Bank Financial Intermediation (MUNFI)".

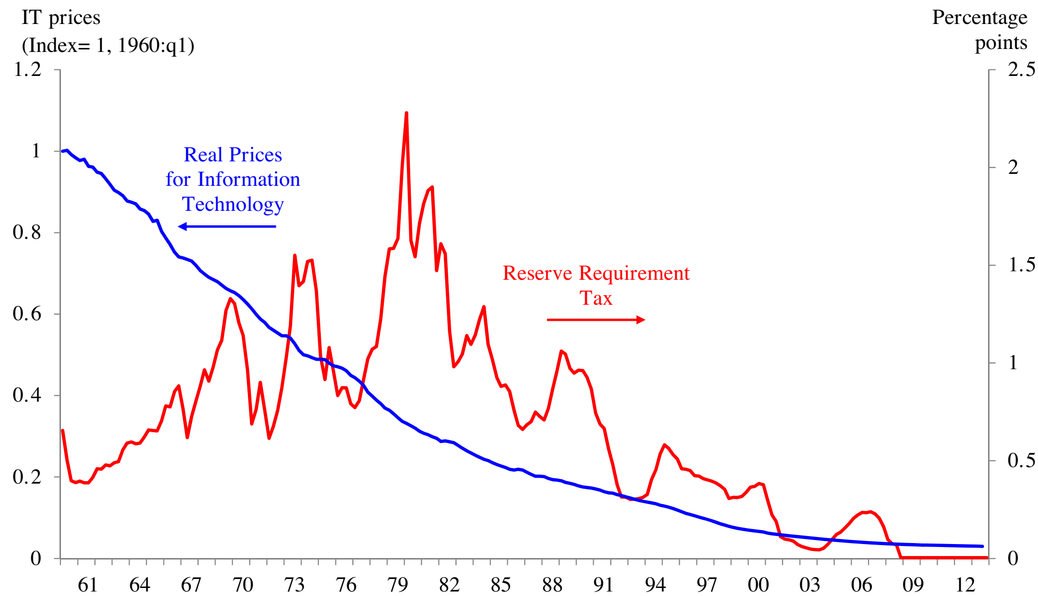

Fig. 2. Real information technology costs and the reserve requirement tax on banks.

Accounts data on nonfinancial corporate debt since 1961:q4 (Fig. 1). *SHADOW* equals the sum of directly issued commercial paper plus finance company loans plus other loans financed by asset-backed commercial paper (securitized C&I loans held by ABS issuers and loans to nonfinancial corporate businesses by ABS issuers) divided by the sum of directly issued commercial paper, bank loans and all other loans (the last category includes finance company loans and ABS-funded loans).[7] The regression models start in 1963:q1, because shifts in underlying source data and sampling techniques created sample breaks in *SHADOW* during the late 1950s and early 1960s.

3.2.2. Long-run information and transactions costs

The rise of shadow banking in recent decades partly stems from the erosion of banks' informational and transactions cost advantages over nonbanks, owing to improvements in technology (see Edwards and Mishkin, 1995; Mishkin, 2009) that plausibly enable borrowers to more easily provide hard information that allows them to "shop" among traditional and shadow banks for credit (Ratnovski, 2013). Studies of the rise of mutual funds stress the role of falling transactions costs at nonbanks stemming from improvements in overall financial sector productivity (Duca, 2000, 2005). To parsimoniously track the influence of broad declines in information costs, which likely track declines in transactions costs, long-run models include a measure of information technology prices. The implicit price deflator for information processing equipment is deflated by the overall GDP chain price deflator to construct *RPIT* (Fig. 2), a relative price measure that should be negatively related to the security-funded share of business credit because its declines should generally reflect the factors that reduce the informational and transactions cost advantages of bank over nonbank intermediaries.

3.2.3. The burden of reserve requirements

The literature has long recognized that reserve requirements imposed a disadvantage on banks that spurred the growth of money market mutual funds and other alternatives to bank deposits (Kanatas and Greenbaum, 1982; Duca, 1992; Rosengren, 2014). The reserve requirement tax can be proxied by nominal interest rates until the Fed paid interest on reserves, in 2008:q4. However, the three-month T-bill rate (*3monTR*) was integrated of order 2 if changes in reserve requirements are ignored. A more precise measure calculates the reserve requirement tax (*RRTAX*) as the product of the three-month T-bill rate and the highest reserve requirement (Fig. 2) on banks in central reserve city (large) banks, adjusted for sweep accounts (Anderson and Rasche, 2001; Dutkowsky and Cynamon, 2003) that shift balances overnight out of reservable checking accounts into money market deposit accounts (MMDAs) to avoid reserve requirements.[8] The reserve requirement tax equals 0.01% over 2008:q4–2013:q3 reflecting near zero short-term Treasury bill rates and the payment of similar interest on reserves.

The reserve requirement burden was high in the 1970s through early 1980s, but has since fallen to record low levels after the financial crisis (Fig. 2). Changes in the reserve requirement tax, which had favored shadow banking in the 1970s and early 1980s, have tempered the growth of shadow banking, particularly since the 2007 onset of the financial crisis.

3.2.4. Deposit, money market mutual fund, and credit regulations

During the era of Regulation Q ceilings on deposit rates that banks could offer, the institutions lost market share to commercial paper and security-funded lenders when market interest rates rose above deposit rate ceilings. The inability of banks to offer interest rates in line with market interest rates induced households and other investors to shift funds from banks, encouraging banks to tighten their credit standards, consistent with the findings of

[7] In the Financial Accounts of the U.S., the following denominator components are from the balance sheet (Table B.103) for nonfinancial corporations: commercial paper (line 26), depository institution (bank) loans (line 29), and other loans and advances (line 30). The following numerator components include commercial paper (from Table B.103: line 26) and from details on other loans and advances in Table L216, finance company loans to nonfinancial corporations (line 33) securitized loans to nonfinancial corporations bought (but not originated) by ABS issuers (line 31), and loans to nonfinancial corporate loans originated by ABS issuers (line 39).

[8] The adjustment equals one minus the ratio of swept balances to the sum of swept balances, reservable demand deposits, and reservable other checkable deposits (Federal Reserve Bank of St. Louis, 2010). The adjustment is consistent with the calculation of the reserve requirement tax in that the estimated reduction in required reserves balances of about 10% of sweep balances (St. Louis Federal Reserve Bank, 2010) roughly equals the maximum 10% marginal reserve requirement for large banks, the ratio gauging the reserve requirement tax.

Duca et al. (2012). One variable to track these effects is Duca's (1996) measure of how much Regulation Q ceilings on retail deposit interest rates were binding until Regulation Q ended in the early 1980s. *REGQ* controls for short-run disintermediation effects not tracked by interest rates or measures of the user cost of capital (Duca and Wu, 2009), which are likely to increase the shadow share of short-term business. *REGQ* also controls for the introduction of some semi-deregulated bank retail deposits in the late 1970s (e.g., money market certificates and small saver certificates).[9]

One innovation induced by deposit rate ceilings and reserve requirements was the creation of money market mutual funds (MMMFs) in 1971 in the U.S. that could pay market-determined interest rates. These funds were not sizable until about 1973, and check-writing features on MMMFs for households were introduced in the late spring of 1974 by Fidelity. By offering investors a liquid way of investing in commercial paper, MMMFs lowered the costs of funding commercial paper relative to bank loans. Partly to counter this drain on the banking system, banks were allowed to offer money market deposit accounts (MMDAs) in 1982:q4. This resulted in inflows into bank deposits from MMMFs and other assets that positively affected money demand (Duca, 2000) and the availability of bank loans (Aron et al., 2012).

To control for these two innovations in a parsimonious way, a variable (*MMAdvantage*) is included that equals 1 over 1974:q2–1982:q3, a period when security-funded business credit was positively affected by the presence of MMMFs and the absence of MMDAs. Because *MMAdvantage* enters as a long-run determinant of the t-1 lagged error-correction term, it is defined as equaling 1 in 1974:q2. In addition, two additional short-term impact variables are included. One (*DMMMF*) equals 1 in 1974:q2, -1 in 1974:q3, and 0 otherwise to control for the initial jump and fallback in the security-funded share around the introduction of MMMFs in 1974. The second impact variable (*DMMDA*) equals 1 in 1982:q4 and 0 otherwise.

Finally, another major short-term regulatory action affecting business financing sources was the imposition and lifting of bank credit controls in 1980:q2 and 1980:q3, respectively, which caused a short-lived shift of business finance to security markets in 1980:q2 that unwound in 1980:q3. To capture this short-run effect, models included *DCON* = 1 in 1980:q2, −1 in 1980:q3, and 0 otherwise. Reflecting its short-run, temporary influence on the structure of finance, *DCON*'s inclusion did not affect other coefficient estimates or the qualitative results.

3.2.5. The relative burden of capital requirements

The literature has long emphasized how shadow banking has been affected by the relative burden of capital requirements on loans versus asset-backed securities held in bank portfolios or on bank versus nonbank assets (Kanatas and Greenbaum, 1982; Pennacchi, 1988). The relative burden of required equity capital-to-asset ratios for business credit across commercial and investment banks differs across three periods, which can be tracked by the differential in minimum capital requirements for commercial bank and shadow bank credit at the margin.

From 1981 to 1984, most commercial banks faced an official minimum 5% leverage ratio (see Wall and Peterson, 1987),[10] and from 1984 to 1989 this minimum rose to 5.5% under the International Lending Supervision Act of 1983. The average capital equity-to-assets ratio for banks was around 6% between the early 1970s until the Basel I Accords were implemented in 1990, providing a cushion over regulatory minimums. From the early 1960s to the early 1970s, the ratio was around 7%. This, however, likely reflected the greater share of smaller banks—whose higher idiosyncratic risk likely induced higher cushions over unofficial required minimums—during a period that predated the partial consolidation of banking amid the rise of bank holding companies.[11] Effectively, C&I loans held in portfolio by large and medium-sized banks faced a 5% minimum capital ratios before 1985 and 5.5% between 1985 and 1989, respectively, whereas nonbank financial intermediaries faced no regulatory minimums and many investors could purchase commercial paper having no capital requirements. During these two respective periods, the marginal regulatory capital differential between bank and shadow bank short-term credit was arguably 5 and 5.5% points, respectively.

Basel I raised the capital requirement on most bank loans held in portfolio from 5.5% to 8% in 1990, encouraging the rise of shadow banking by inducing securitization.[12] Asset-backed securities were held either directly by investors or indirectly through money market and other mutual funds, and later by special investment vehicles (SIVs) during the structured finance boom of the 2000s. Partly because the securitization of business loans was not highly developed at the time, Basel I had a role in the credit crunch of the early 1990s (see Bernanke and Lown, 1991; Berger and Udell, 1994). Nevertheless, at the margins, Basel I effectively raised the gap between minimum capital ratio requirements for bank C&I loans and shadow bank credit from 5.5% to 8% points, thereby promoting shadow banking.

The regulatory playing field became relatively less favorable to shadow banking after the passage of the Dodd-Frank Act (DFA), which had three provisions relevant to the shadow bank share. First, the rules enacting DFA raised the minimum capital requirement on C&I loans held in portfolio to 10.5%. Second, the act required banks to hold capital against losses of up to 5% on securitized assets and subjected them to regulatory stress tests that involved ensuring that banks maintained equity capital to withstand a scenario of severe recession and lower asset prices. The combination of these last two provisions essentially required loan originators to hold capital equal to 5% of securitized C&I loans. On top of these capital requirements, banks are also required to build up in good times an additional 2.5% capital conservation buffer to protect their exposures to loans—both on- and off-balance sheet. At the margin, the combination of these provisions effectively narrows the difference between the minimum capital ratios on C&I loans held in portfolio and those securitized from 8% to 5.5% (10.5% on loans minus a 5% reserve on securitized C&I loans).[13]

This study parsimoniously tracks the shifts in capital regulatory arbitrage effects in an econometric framework with the variable *CapDif* (Fig. 3), which equals the differential in minimum capital requirements for commercial bank and shadow bank credit at

[9] There were ceilings on large-time deposits longer than 90 days until 1974:q2. Up through that quarter, the time series movements on bindingness of Regulation Q effects on large time deposits mirrored those from regulations on retail deposits. For this reason a separate bindingness measure for large time deposits was statistically insignificant in other runs not shown, as was a dummy for the lifting of large time deposit rate ceilings in 1974:q2.

[10] Small community banks faced a 6% minimum, and larger regional and money center banks faced a 5% minimum.

[11] Bank holding companies (BHCs) expanded in the late 1960s, aided by the Bank Holding Company Act of 1970. Omarova and Tahyar (2011–2012, p. 148) note that the accompanying rise of BHCs was partly motivated by a desire to economize on equity capital held at individual banks owned by a BHC. This resulted in a minor drop in the banking industry's aggregate capital ratio from 7% in the 1960s to 6% by the early 1970s.

[12] One motive for this was to promote mortgage securitization as a means of cushioning the availability of U.S. home mortgages following closure of many troubled savings and loan institutions in the late 1980s and early 1990s.

[13] Near DFA's passage, the shadow share fell. DFA toughened rules on derivatives to improve their transparency to lower their systemic risk, which was seen as contributing to the rise of shadow banks and their role in the financial crisis (Duca et al., 2010). DFA imposed liquidity rules on systemically important bank *and* nonbank financial firms to restrict duration risk and systemic risks posed by asset maturity transformation (Gorton and Metrick, 2012).

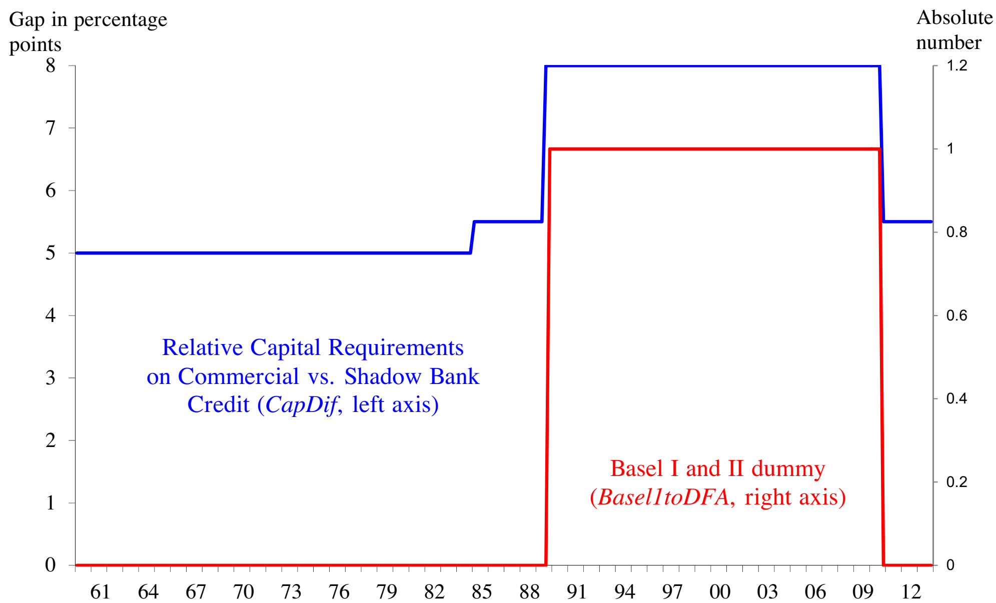

Fig. 3. Tracking the relative impact of capital regulations on commercial bank versus shadow bank funding.

the margin. For the pre-Basel period when C&I loan securitization was nonexistent, the marginal alternative to bank C&I loans that faced a 5% minimum capital ratio before 1985 and 5.5% for large banks between 1985q1 and 1989q4 were loans by finance companies and commercial paper that had no regulatory minimums, implying that *CapDif* should equal 5 and 5.5% before 1985 and between 1985 and 1989, respectively. Between the enactments of Basel I and DFA, the margin of substitution shifted to a choice between bank loans held in portfolio facing an 8% minimum total capital ratio and securitized loans facing no capital minimums, which spurred the rise of ABS-financed bank loans and commercial paper. Accordingly *CapDif* equals 8% during this era. And in the DFA era, *CapDif* equals 5.5% to reflect the narrowing of the effective regulatory capital differentials between C&I loans held in portfolio and those securitized by loan originators. Because of *CapDif* enters the error-correction models with a $t-1$ lag and the regulations it reflects were announced ahead of implementation, *CapDif* equals 5 before 1985, 5.5 up until 1989:q3, 8 between 1989:q4 and 2010:q3, and 5.5 since 2010:q4.[14] To control for the short-run effects of DFA and pressure on financial institutions to conform quickly with it, an implementation dummy (*DFADUM*) equal to 1 in 2010:q4 was added (its inclusion barely affects long-run coefficients while tracking an unusual outlier).

3.2.6. Tracking the impact of risk premia and procyclical influences on business credit sources

The safety net for commercial banks favors them over shadow banks in periods of economic distress and high risk premia. To control for such effects, two types of variables are included: forward-looking business cycle indicators and measures of liquidity and default premia. Of the former, the best performing real-time indicator is the spread between the 10-year and one-year Treasury yields (*YC*),[15] reflecting its usefulness as a leading economic indicator (Estrella and Mishkin, 1998, and Hamilton and Kim, 2002) and perhaps for tracking incentives to "reach for yield" when short-term interest rates are low (Stein, 2013). The $t-3$ lag outperformed other lags, and this term premium outperformed those that replaced the one-year Treasury rate with either the federal funds rate or the three-month Treasury rate.

Liquidity and default risk premia are tracked by spreads between A-rated corporate and 10-year Treasury bond yields (*A10TR*), consistent with evidence that such spreads reflect a combination of swings in default and liquidity risk premiums dating back to at least Jaffee (1975) and noted in more recent studies (e.g., Friewald et al., 2012). Wider spreads are less of a threat to the funding of bank loans, as banks had access to insured deposits and Fed liquidity facilities before mid-October 2008. As a result, when such spreads are high, the price and non-price terms of market debt that typically funds shadow banks are high relative to those of bank loans, implying a negative relationship between the shadow bank share and bond spreads consistent with the negative relationships seen between commercial paper and bond spreads during the Great Depression (Duca (2013b)) and Great Recession (Duca (2013a)).[16]

Because liquidity spreads may not track all flights to quality, event risk dummies were included in some regressions. These included *PennCentral*, equal to 1 in the quarter when the Penn Central railroad defaulted on its commercial paper, −1 in the next quarter when the flight to quality unwound, and 0 otherwise.[17] A similar dummy, *StockCrash87*, equals 1 when the stock market crashed in 1987:q4. Another event risk dummy was for the near

[14] A shift dummy for the SEC's easing of capital requirements on investment banks (equal to 1 from 2004:q4 to 2010:q3) was statistically insignificant—as was a similarly timed shift dummy for potential Basel II effects—and neither was not included in the models reported in Table 1.

[15] The components of and weights on the index of leading economic indicators have changed so much over time that the index is not a real-time indicator, in contrast to the interest rates used to construct yield curve variables.

[16] *A10TR* outperformed the Baa corporate and 10-year Treasury yield sread, perhaps reflecting the relative thinness of trading in Baa-rated firms that sometimes pose the risk of being downgraded to junk. *A10TR* can be consistently measured, unlike spreads between commercial paper and Treasury bill rates. *A10TR* also outperformed the TED spread (three-month Libor minus three-month Treasury bill rates), which was statistically insignificant in other runs. This could reflect that the TED spread may pick up a combination of general market risk premia and more specific shocks to commercial banks relative to other financial firms, implying an ambiguous effect on the shadow share.

[17] A similar dummy for the failure of the Continental Illinois bank was insignificant in other runs, as was the case for impact dummy variables for the onset of the Asian Crisis (1997q2), the LTCM/Russian Default (1998q3), and the Internet bust of 2000 (2000q1 or 2000q2).

outright default of New York City municipal debt in 1975:q4 (*NYCDef* = 1 that quarter, 0 otherwise), which disrupted short-term debt markets in late 1975. The last dummy, *DBNP*, equals 1 in 2007:q4, typically seen as the start of the 2007–09 housing and financial crisis in the U.S., triggered when three hedge funds suspended redemptions because subprime positions could not be priced to market (Duca et al., 2010). Of these variables, three (*PennCentral*, *NYCDef*, and *DBNP*) are associated with events that initially more notably affected shorter-term debt markets relevant for funding shadow banking and were not fully reflected in corporate bond risk premia. The stock market crash of 1987 was a more general shock to the financial system as it initially raised fears that an economic depression might ensue. Since commercial banks have more safety net support than shadow banks, tail risk events could induce investors to shift their holdings of shorter-term assets from uninsured debt into insured bank deposits or Treasury bills to an extent not fully reflected in corporate bond spreads. Accordingly, the event risk variables are expected to have negative coefficients, reflecting temporary negative shocks to shadow bank funding. In regressions not shown, event risk dummies for the resolution of insolvent savings and loans (S&Ls) in mid-1989 were statistically insignificant. This likely and partly reflects that S&L regulations had induced them to specialize first in making in loans for residential mortgages and later for commercial real estate and energy industry related energy, so their closure barely affected C&I lending.

4. Results for Modeling the shadow banking share of short-term business credit

Cointegration models of the security-funded short-run credit mix variable (*SHADOW*) were run owing to unit roots in *SHADOW* (Table 1), the reserve requirement tax, the information technology price series, regulatory shift, and relative minimum capital ratio variables.[18] Table 1 presents results from models using *CapDif* to track long-lasting capital regulatory shifts. Each model has a sample starting in 1963:q1 to avoid data distorted by sample breaks over 1959–61 stemming from changes in how the Financial Accounts of the U.S. sampled and measured balance sheet components. Models 1–3, 5 and 7 are estimated over the full sample of 1963:q1–2013:q3, while models 4 and 6 estimate the preferred model 3 over the pre-crisis period of 1963:q1–2006:q4. Models 1–3 use different controls for short-run risk factors. Models 1–4 and 7 are estimated as VEC models that allow the long-run variables to be endogenous to each other. As discussed below, Models 5 and 6 assume that information costs, the reserve requirement tax, and MMMF/MMDA regulations are weakly exogenous to the shadow share, but allow for long-run endogenous feedback between the shadow share and regulatory capital arbitrage.

Various combinations of short-run factors were tested and a sequential general-to-specific procedure for dropping the most insignificant short-run controls (as reported elsewhere) was adopted in constructing the preferred model, number 3. Table 1 orders the models to illustrate the impact on a baseline model of adding short-run factors in building to preferred model 3.

As shown in Table 1, all seven models include the reserve requirement tax and the real price of information technology as long-run endogenous variables in the cointegrating vector. Because the money fund and capital regulatory variables were long-lasting, they were included in the cointegrating vector to more accurately gauge long-run relationships. Models 1–6 contain a core and common set of short-run variables to handle general business cycle effects (*YC*), risk premia effects (ln(*ATR10*)), shorter-term regulatory effects involving disintermediation (*REGQ*), and impact dummies for the introduction of MMMFs, MMDAs, and the Dodd-Frank Act (*DMMMF*, *DMMDA*, and *DFADum*, respectively). To these variables, model 2 adds a dummy for the commercial bank credit controls of 1980 (*DCON*) and model 3 also adds a set of event risk variables (*DBNP*, *StockCrash87*, *PennCentral*, and *NYCDef*). Model 7 omits the yield curve (*YC*) and risk premia (ln(*ATR10*)) variables from model 1, to examine whether the long-run results are robust to the exclusion of these variables, which one might view as endogenous.

The Johansen (1991, 1995) procedure is used to estimate cointegrating vectors for the log-level of *SHADOW* in the first stage, from which error-correction terms are constructed to use in a second-step VAR in first differences for modeling short-run movements. For each model, unique and statistically significant cointegrating vectors are estimated, implying that a unique long-run relationship exists between the shadow share and its long-run determinants that yields stationary (trendless) residuals. This is implied by the Trace and Max-Eigenvalue statistics reported in Table 1. For each model, these statistics significantly reject the hypothesis that there are no cointegrating vectors, but do not reject the hypothesis that there are not more than one cointegrating vectors. The estimation allows for deterministic trends in the long-run variables but not in the cointegrating vector. For models 1–6, a lag length of 5 was selected to maximize the Akaike Information Criterion subject to obtaining a unique vector and clean residuals.

In each model, significant, long-run coefficients indicate that regulations that disadvantaged banks (*MMAdvantage* and *CapDif*) increased the shadow banking system's share of business credit. Also, as expected, there is a negative relationship between the real price of information technology and the shadow bank share. Higher IT prices suggest that information is more costly and transactions costs are higher, ceteris paribus. By implication, informational and transactions cost advantages of bank over shadow bank credit are greater as IT prices are higher. In all models, the reserve requirement tax variable (ln*RRTAX*) has a positive and significant effect on the security market-funded share of short-term business credit. The coefficients on all of the long-run variables are reasonably similar across models 1–7. In another set of runs not reported in the tables, results are robust to replacing the calibrated regulatory arbitrage variable with a dummy variable equal to 1 for the period spanning Basel 1 until the Dodd-Frank Act passed.

In models 1–4, the error-correction term was only significant in models of the change in the shadow share and regulatory arbitrage, prompting two interesting and sensible implications. First, that information costs, the reserve requirement share, and regulations affecting money market mutual funds versus MMDA accounts are weakly exogenous to the shadow share, but the regulatory capital arbitrage variable is not. In other words, long-term movements in the shadow share do not significantly move before those reflecting the cost of information, the reserve requirement tax, and regulation of MMMFs and MMDAs. By comparison, long-run movements in the latter three factors move before those in the shadow share. This

[18] Unfortunately, owing to limited data availability over a 50 year period, little could be done to distinguish between supply and demand factors beyond what is implicit in the modeling strategy. By focusing on modeling the shadow share rather than the level of shadow credit, the model largely abstracts from demand factors that plausibly affect the numerator and denominator of the share variable in the same direction. Also, the long-run drivers of the shadow share are arguably supply-side factors—it is plausible to see capital and reserve requirement regulatory arbitrage effects as affecting the relative supply of shadow versus non-shadow credit. One might argue that the information cost variable plausibly reflects a mix of supply and demand factors, insofar as smaller firms, which tend to borrow more from commercial banks, might account for greater product market share as information costs fall and reduce the scale and/or scope advantages of larger firms that might issue short-term debt. This possible demand side factor works in the same direction as the supply side influence of lower information costs that plausibly shift the relative supply of credit to security funded credit. Nevertheless, the corporate nonfinancial sector's rising share of GDP versus noncorporate, nonfinancial businesses runs counter to this conceivable product market channel effect.

Table 1
Quarterly error-correction models of the change in the shadow bank (security-funded) share of non financial corporate short-term debt.

	Omits *DCON* and event risks	Adds Credit Controls	Adds Event Risks	Pre-Crisis Model 3	Long-Run Feedback Only Between *SHADOW* & *CapDif*		No Cyclical/Event Risks
Sample:	63:1–13:3	63:1–13:3	63:1–13:3	63:1–06:4	63:1–13:3	63:1–06:4	63:1–13:3
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
A. Long-Run Equilibrium Relationships: $lnSHADOW = \lambda_0 + \lambda_1 lnRRTAX + \lambda_2 lnRPIT + \lambda_3 MMadv + \lambda_2 CapDif$							
Constant	−1.1811	−1.2013	−1.1918	−1.1418	−1.1934	−1.1319	−1.2465
$\ln RRTAX_{t-1}$	0.0455**	0.0435**	0.0415**	0.0317*	0.0363**	0.0288*	0.0416**
	(4.98)	(4.70)	(5.22)	(2.60)	(4.53)	(2.36)	(4.53)
$\ln RPIT_{t-1}$	−0.2704**	−0.2654**	−0.2696**	−0.2730**	−0.2641**	−0.2718**	−0.2667**
	(−14.81)	(−14.29)	(−16.83)	(−14.16)	(−16.34)	(−14.10)	(−14.46)
$MMAdvantage_{t-1}$	0.2108**	0.2119**	0.2211**	0.2215**	0.2210**	0.2210**	0.2030**
	(10.09)	(10.01)	(12.25)	(11.74)	(12.14)	(11.71)	(7.22)
$CapDif_{t-1}$	0.0680**	0.0695**	0.0685**	0.0606**	0.0665**	0.0584**	0.0769**
	(7.57)	(7.63)	(8.87)	(6.53)	(8.53)	(6.29)	(6.76)
Trace (1 vec.)	82.9379**	81.4777**	93.4101**	89.8128**	93.4101**	89.8128**	73.7164*
Trace (2 vec.)	28.2365	27.6797	27.3737	33.6108	27.3737	33.6108	35.1784
Max-Eigen (1)	54.7015**	53.7981**	66.0364**	56.2020**	66.0364**	56.2020**	38.5380*
Max-Eigen (2)	15.0508	14.9131	14.4380	17.8640	14.4380	17.8640	20.3628
VEC lag length	5	5	5	5	5	5	6
Chi-square exogeneity					4.1276 (insignificant)	0.6922 (insignificant)	
B. Short-Run Equilibrium Relationships: $\Delta lnSHADOW_t = \alpha_0 + \alpha_1 log(EC)_{t-1} + \beta_i \Delta log(SHADOW)_{t-i} + \theta_i \Delta log(X)_{t-i} + \delta Y_t$							
Constant	−0.0126*	−0.0124*	−0.0103*	−0.0110*	−0.0128**	−0.0121*	0.0028
	(−2.66)	(−2.66)	(−2.39)	(−2.14)	(−2.92)	(2.34)	(0.67)
EC_{t-1}	−0.2391**	−0.2310**	−0.2596**	−0.2667**	−0.2583**	−0.2640**	−0.1698**
	(−6.38)	(−6.26)	(−7.17)	(−6.62)	(−7.04)	(−6.62)	(−4.60)
Regulatory Controls							
$REGQ_{t-2}$ ($\times$100)	1.4550**	1.4031**	1.3708**	1.3476**	1.3553**	1.3426**	0.7360*
	(4.33)	(4.23)	(4.48)	(4.10)	(4.34)	(4.09)	(2.42)
$DCON_t$		0.0368*	0.0380**	0.0419**	0.0385**	0.0422**	0.0429**
		(2.55)	(2.87)	(3.03)	(2.91)	(3.06)	(2.80)
$DMMMF_{t-1}$	0.0501*	0.0514*	0.0554**	0.0577**	0.0556**	0.0578**	0.0509*
	(2.24)	(2.33)	(2.73)	(2.69)	(2.74)	(2.70)	(2.15)
$DMMDA_{t-1}$	−0.0600**	−0.0616**	−0.0600**	−0.0685**	−0.0594**	−0.0685**	−0.0683**
	(−2.75)	(−2.87)	(−3.05)	(−3.22)	(−3.02)	(−3.22)	(−2.97)
$DFADUM_t$	−0.1153**	−0.1161**	−0.1162**		−0.1178**		−0.1035**
	(−5.51)	(−5.62)	(−6.13)		(−6.20)		(−4.76)
Risk Controls							
$\ln ATR_{t-1}$ ($\times$100)	−0.7359*	−0.5712^{+}	−0.7782*	−0.7758*	−0.6785*	−0.7218*	
	(−2.09)	(−1.65)	(−2.42)	(−2.10)	(−2.12)	(−1.96)	
YC_{t-3} ($\times$100)	1.0921**	1.0370**	0.9886**	1.0154**	0.9830**	1.0213**	
	(5.44)	(5.24)	(5.39)	(4.59)	(5.35)	(4.60)	
$DBNP_t$			−0.0578**		−0.0552**		
			(−3.09)		(−2.95)		
$StockCrash87_t$			−0.0715**	−0.0732**	−0.0723**	−0.0732**	
			(−3.67)	(−3.60)	(−3.70)	(−3.59)	
$PennCentral_t$			−0.0317*	−0.0316*	−0.0316*	−0.0315*	
			(−2.45)	(−2.38)	(−2.43)	(−2.37)	
NYCDef			−0.0610**	−0.0577**	−0.0612**	−0.0574**	
			(−3.03)	(−2.70)	(−3.03)	(−2.69)	
Lagged First Differences of Long-Term Variables							
$\Delta\ln SHADOW_{t-1}$	0.0810	0.0962	0.1642*	0.1556*	0.1684**	0.1550*	0.1193^{+}
	(1.27)	(1.45)	(2.64)	(2.18)	(2.69)	(2.18)	(1.65)
$\Delta\ln SHADOW_{t-2}$	0.1737*	0.1697*	0.1864**	0.2009**	0.1912**	0.2018**	0.1902**
	(2.62)	(2.60)	(3.08)	(2.95)	(3.14)	(2.96)	(2.72)
$\Delta\ln RRTAX_{t-1}$	−0.0058	−0.0064	−0.0059	−0.0159	−0.0053	−0.0160	0.0010
	(−0.83)	(−0.91)	(−0.93)	(−0.96)	(−0.83)	(−0.97)	(0.14)
$\Delta\ln RRTAX_{t-2}$	0.0039	0.0049	0.0028	−0.0030	0.0036	−0.0023	0.0118^{+}
	(0.55)	(0.71)	(0.45)	(−0.17)	(0.57)	(−0.13)	(1.65)
$\Delta\ln RPIT_{t-1}$	−0.2833	−0.3173	−0.2697	−0.3516^{+}	−0.3066	−0.3693^{+}	−0.3129
	(−1.33)	(−1.52)	(−1.40)	(−1.67)	(−1.58)	(−1.75)	(−1.38)
$\Delta\ln RPIT_{t-2}$	0.0258	0.0848	0.1578	0.2239	0.1387	0.2150	0.1575
	(0.11)	(0.35)	(0.71)	(0.92)	(0.62)	(0.89)	(0.61)
$\Delta MMAdvantage_{t-1}$	−0.0418*	−0.0404*	−0.0482*	−0.0461*	−0.0500*	−0.0463*	−0.0276
	(−2.05)	(−2.00)	(−2.56)	(−2.27)	(−2.64)	(−2.27)	(−1.30)
$\Delta MMAdvantage_{t-2}$	−0.0094	−0.0082	−0.0160	0.0191	−0.0176	−0.0192	−0.0016
	(−0.46)	(−0.41)	(−0.85)	(0.97)	(−0.93)	(−0.97)	(−0.07)
$\Delta CapDif_{t-1}$	−0.0018	−0.0019	−0.0045	−0.0083	−0.0037	−0.0078	−0.0049
	(−0.30)	(−0.32)	(−0.80)	(−1.08)	(−0.66)	(−1.01)	(−0.75)
$\Delta CapDif_{t-2}$	−0.0022	−0.0020	−0.0025	0.0006	−0.0017	0.0012	−0.0052
	(−0.35)	(−0.34)	(−0.45)	(0.08)	(−0.30)	(0.16)	(−0.81)

Table 1 (*continued*)

	Omits *DCON* and event risks	Adds Credit Controls	Adds Event Risks	Pre-Crisis Model 3	Long-Run Feedback Only Between *SHADOW* & *CapDif*		No Cyclical/Event Risks
Sample:	63:1–13:3	63:1–13:3	63:1–13:3	63:1–06:4	63:1–13:3	63:1–06:4	63:1–13:3
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Summary Stats.							
Adjusted R^2	.3374	.3572	.4597	.3873	.4581	.3863	.2759
S.E.	0.0202	0.0199	0.0182	0.0186	0.0183	0.0186	0.0211
VECLM(1)	17.65	15.73	13.96	14.66	20.27	15.33	18.65
VECLM(2)	24.01	25.83	25.04	16.39	32.20	17.63	34.01
VECLM(4)	27.27	26.66	28.93	27.66	35.90^{+}	29.16	22.99
VECLM(6)	15.61	15.91	30.83	36.62	36.42^{+}	37.19^{+}	17.33

Unit Root Tests (1962:q1–2013:q3)

	Level (SIC lag in parentheses)	5% Critical level for lag	1% Critical level for lag
ln*SHADOW*	−0.448450 (0)	−3.431682	−4.003005
Δln*SHADOW*	−5.174103** (7)	−3.431682	−4.003005
ln*RRTAX*	−1.192915 (0)	−3.432005	−4.003675
Δln*RRTAX*	−12.32873** (0)	−3.432005	−4.003675
ln*RPIT*	1.795024 (1)	−3.432005	−4.003675
Δln*RPIT*	−7.298104** (0)	−3.432005	−4.003675

Notes: $^{+}$, *, and ** denotes significant at the 90%, 95%, and 99% level, respectively. *t*-Statistics are in parentheses. A lag length of 5 minimized the AIC in models 1–7, and yielded unique, significant vectors allowing time trends in the variables and, in most cases, clean residuals. Models 5 and 6 differ in treating information costs, the reserve requirement tax, and money market fund regulations as weakly exogenous to the shadow share, but treat the shadow share and the regulatory capital arbitrage variables as being endogenous to each other. Lag lengths for unit root tests are based on the SIC and all included a constant and a trend. Coefficients on lags of difference terms longer than $t-2$ are omitted to conserve space.

evidence of long-run Granger causality (see Granger and Lin, 1995) accords with the view that movements in information costs and regulations are largely exogenous to the shadow share.

The second implication is that long-run movements in the shadow share and the incentives for regulatory arbitrage have long-run feedbacks on each other. The feedback from the shadow share to the regulatory arbitrage variable is consistent with the interpretation that as the shadow share grew too large and ultimately threatened financial stability in the recent crisis, it induced regulatory changes that undid some of the incentives for regulatory capital arbitrage, such as the "skin in the game" provisions of DFA limiting both moral hazard and regulatory arbitrage incentives to securitize. Reflecting these findings, Models 5 and 6 allow for long-run feedback from the shadow share onto regulatory capital arbitrage, but impose that information costs, the reserve requirement tax, and MMMF/MMDA regulations are weakly exogenous to the shadow share. This restriction is not rejected according to Chi-square statistics.

The short-run models of the change in the shadow bank share account for long-run relationships by including an error-correction term equal to the t-1 gap of the actual security-funded debt share minus the estimated long-run equilibrium. Across the short-run models in the lower-panel of Table 1, the error-correction coefficients are highly significant, with an expected negative sign. Thus, if actual shadow share exceeded its equilibrium in time t-1, this would exert a negative impact on the time t change in the shadow share, as expected. In every model, the estimated speeds of adjustment are similar, implying that roughly 23–27% of disequilibria are eliminated on average per quarter. This speed is sensible given the limited maturity of short-term business credit and the large shifts in the shadow share over the past five decades.

Several noteworthy, expected patterns of short-run effects arise across the models. First, the Regulation Q variable is significant, with the bindingness of retail deposit ceilings having a highly significant and expected positive short-run effect on shadow bank share. Second, the introduction of MMMFs raised the shadow bank share, while the introduction of MMDAs and the passage of DFA had negative impacts. Third, the yield curve (*YC*) is highly significant and positively signed and the bond spread is at least marginally significant with a negative sign.

The first three models differ in how they control for changes in some types of short-run factors. To Model 1, Model 2 adds the dummy for the credit controls imposed on commercial banks in 1980:q2, which has a highly significant and positively signed coefficient. Other coefficients were not notably affected by this change, as seen by comparing Models 1 and 2. To Model 2, model 3 adds the four risk event variables for the Penn Central bankruptcy, the near explicit default of New York City in 1975, the stock market crash of 1987, and the BNP hedge fund event of August 2007. As could be expected, each of these event risk variables is significant, with the shadow bank share of short-term business credit swinging by three percentage points in response to the Penn Central default and by a larger six percentage points in response to the near-default of New York City, the 1987 stock market crash, and August 2007 BNP subprime event. A separate dummy for the failure of Lehman was statistically insignificant, perhaps reflecting that much of the effect was picked up by the sharp spike in the corporate bond spread at that time and because the lender of last resort actions of the Federal Reserve and Treasury buttressed shadow banking by supporting money market mutual funds and the commercial paper market (Duca, 2013b). While models 1–3 have sensible short- and long-run properties and clean residuals, Model 3 is considered the preferred specification because it has the best model fit of these three models and more comprehensively accounts for event risks.

A challenge to incorporating regulatory regimes into time series models is that the coefficient estimates may not be robust to the samples used. While some of this is inevitable given the nature of regime shifts, it is important to assess the reliability of coefficient estimates. Balancing these two considerations, model 4 was re-estimated over the pre-crisis period of 1963:q1–2006:q4 (necessitating the omission of the *DBNP* and *DFADum* variables). Comparing models 3 and 4 reveals no difference in qualitative findings and small differences in estimated coefficients, implying that the preferred specification is robust to including the recent crisis.

So far, models 1–4 were estimated in a vector-error correction framework in which the four variables in the cointegrating vector were allowed to affect each other in the long-run, allowing for a great deal of feedback—though only the impact on the shadow share is shown in the tables to focus the analysis on the shadow share. In fact, one could not reject the null hypothesis of no

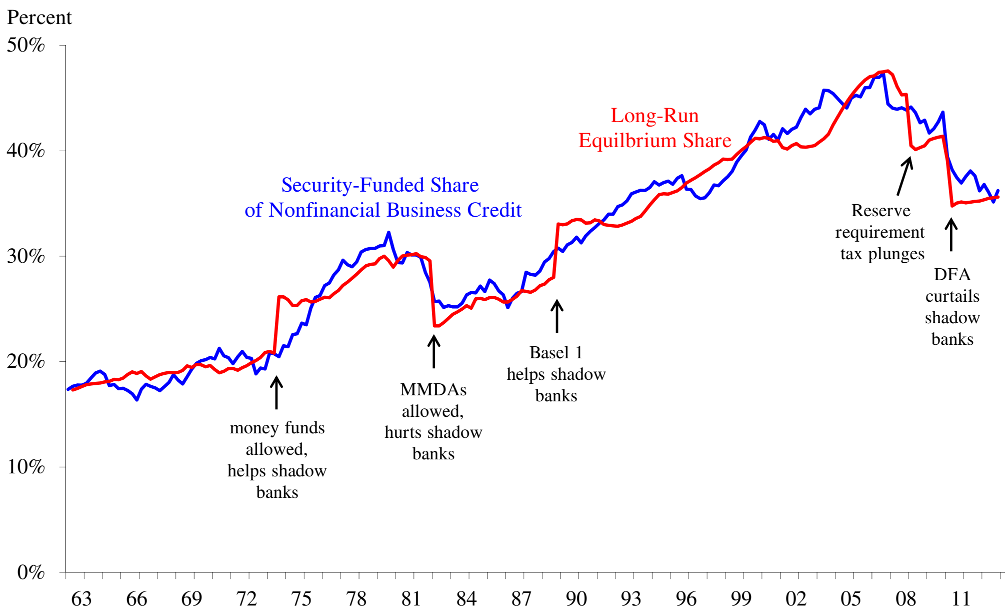

Fig. 4. Shadow bank share of nonfinancial business credit generally tracked well by the preferred model (model 3).

Table 2
Assessing time trends in quarterly error-correction models of the change in the shadow bank (security-funded) share of nonfinancial corporate short-term debt.

			Long-Run Time Trend Replaces Info. Costs	
Sample: Variable	63:1–13:3 Model 1	63:1–13:3 Model 2	63:1–13:3 Model 3	63:1–13:3 Model 4
A. Long-Run Equilibrium Relationships: $lnSHADOW = \lambda_0 + \lambda_1 lnRRTAX + \lambda_2 lnRPIT \text{ or } TIME + \lambda_3 MMadv + \lambda_2 CapDif$				
Constant	−1.1811	−1.1918	−2.3255	−2.3557
$\ln RRTAX_{t-1}$	0.0455**	0.0415**	0.0386**	0.0287*
	(4.98)	(5.22)	(3.09)	(2.35)
$\ln RPIT_{t-1}$	−0.2704**	−0.2696**		
	(−14.81)	(−16.83)		
TIME*100			0.4980**	0.4666**
			(10.14)	(9.70)
$MMAdvantage_{t-1}$	0.2108**	0.2211**	0.1859**	0.2000**
	(10.09)	(12.25)	(5.94)	(6.65)
$CapDif_{t-1}$	0.0680**	0.0685**	0.0660**	0.0758**
	(7.57)	(8.87)	(4.96)	(5.87)
Trace (1 vec.)	82.9379**	81.4777**	62.1453+	64.7987*
Trace (2 vec.)	28.23645	27.6797	26.1913	26.6647
Max-Eigen (1)	54.7015**	53.7981**	35.9540*	38.1340*
Max-Eigen (2)	15.0508	14.9131	21.2945	21.9342
VEC lag length	5	5	7	7
B. Short-Run Equilibrium Relationships: $\Delta lnSHADOW_t = \alpha_0 + \alpha_1 log(EC)_{t-1} + \beta_i \Delta log(SHADOW)_{t-i} + \theta_i \Delta log(X)_{t-i} + \delta Y_t$				
EC_{t-1}	−0.2391**	−0.2596**	−0.1965**	−0.1877**
	(−6.38)	(−7.17)	(−5.60)	(−5.61)
Summary Stats.				
Adjusted R^2	.3374	.4597	.3049	.4021
S.E.	0.0202	0.0182	0.0207	0.0192
VECLM(1)	17.65	14.66	14.29	7.74
VECLM(2)	24.01	16.39	15.99	14.31
VECLM(4)	27.27	27.66	14.04	14.75
VECLM(6)	15.61	36.62	12.95	24.42+

Notes: +, *, and ** denotes significant at the 90%, 95%, and 99% level, respectively. *t*-Statistics are in parentheses. Lag lengths of 5, 5, 7, and 7 minimized the AIC in models 1–4, respectively, and yielded unique, significant vectors allowing time trends in the variables and, in most cases, clean residuals. Coefficients on lags of difference terms are omitted to conserve space.

feedback from the shadow share onto the money fund advantage variable and real information costs.[19] Nevertheless, one could reject the hypothesis of no feedback of the shadow share on the regulatory capital requirement arbitrage variable—in other words, that changes in the shadow share temporally preceded changes in capital regulation, consistent with the interpretation that regulation reacts, with a lag, to major economic trends or events. As another robustness check, models 5 and 6 use the same set of short-run controls and sample as models 3 and 4, respectively, but are estimated imposing the restriction that information costs, the reserve requirement tax, and regulations affecting money funds and MMDAs are weakly

[19] If the error-correction term is insignificant in models of changes in ln*RPIT* and *MMAdvantage*, then in levels these variables are weakly exogenous to the shadow share (are not temporally granger caused by the shadow share in the long-run). The error-correction term was significant in the model of changes in the capital arbitrage term.

Table 3
Quarterly error-correction models of the change in the non-financial corporate shadow bank (security-funded) debt relative to output.

	Omits *DCON* and event risks	Adds Credit Controls	Adds Event Risks	Pre-Crisis Model 3	*MMAdv.* added to Model 3	Long-Run Time Trend Replaces Info. Costs	
Sample:	63:1–13:3	63:1–13:3	63:1–13:3	63:1–06:4	63:1–13:3	63:1–13:3	63:1–13:3
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
A. Long-Run Equilibrium Relationships: $lnSHADOWGDP = \lambda_0 + \lambda_1 lnRRTAX + \lambda_2 lnRPIT + \lambda_3 MMadv + \lambda_2 CapDif$							
Constant	−2.9834	−2.9443	−2.8617	−2.4713	−2.8682	0.5434	0.5467
$\ln RRTAX_{t-1}$	0.3444**	0.3371**	0.3167**	0.3088**	0.3144**	0.2267**	0.2167**
	(8.70)	(8.62)	(9.29)	(9.82)	(8.73)	(9.21)	(10.02)
$\ln RPIT_{t-1}$ 1–4	−0.6259**	−0.6123**	−0.5817**	−0.4942**	−0.5812**	0.0101**	−0.0097**
Time mod.6–7	(−9.60)	(−9.49)	(−10.32)	(−10.35)	(−9.48)	(12.07)	(−13.00)
$MMAdvantage_{t-1}$					0.0014		
					(0.02)		
$CapDif_{t-1}$	0.0682*	0.0696**	0.0713*	0.0976**	0.0697**	0.0435^{+}	0.0525*
	(2.07)	(2.14)	(2.51)	(3.01)	(9.48)	(1.73)	(2.37)
Trace (1 vec.)	61.3610**	60.5123**	65.0331**	55.1240**	74.4873*	49.9775**	53.9508**
Trace (2 vec.)	28.9286	28.6553	28.2939	29.4306	36.9208	19.9369	18.5609
Max-Eigen (1)	32.4324*	31.8571*	36.7391**	25.6934**	37.5665**	30.0407*	35.3899*
Max-Eigen (2)	18.8445	18.6299	18.4000	16.5294	20.1517	17.8471	16.4723
VEC lag length	5	5	5	5	5	5	5
B. Short-Run Equilibrium Relationships: $\Delta lnSHADOWGDP_t = \alpha_0 + \alpha_1 log(EC)_{t-1} + \beta_i \Delta log(SHADOWGDP)_{t-i} + \theta_i \Delta log(X)_{t-i} + \delta Y_t$							
Constant	−0.0011	−0.0013	−0.0036	−0.0059	−0.0029	−0.0017	0.0033
	(−0.19)	(−0.23)	(−0.65)	(−0.90)	(−0.51)	(−0.49)	(0.94)
EC_{t-1}	−0.0682**	−0.0681**	−0.0790**	−0.0872**	−0.0764**	−0.0972**	−0.1050**
	(−4.28)	(−4.18)	(−4.68)	(−3.01)	(−4.38)	(−4.47)	(−4.74)
Regulatory Controls							
$REGQ_{t-1}$ (×100)	0.8651*	0.7979*	0.9666**	0.8181*	0.8946*	0.7852*	0.9140*
	(2.42)	(2.15)	(2.65)	(2.14)	(2.41)	(2.17)	(2.55)
$DCON_t$		0.0281^{+}	0.0283^{+}	0.0249	0.0292^{+}		0.0281^{+}
		(1.62)	(1.69)	(1.42)	(1.73)		(1.70)
$DMMMF_t$	0.0647*	0.0656*	0.0661**	0.0676*	0.0730*	0.0586*	0.0560*
	(2.52)	(2.57)	(2.67)	(2.59)	(2.03)	(2.38)	(2.35)
$DMMDA_t$	−0.0628*	−0.0643*	−0.0645**	−0.0700**	−0.0657**	−0.0671**	−0.0678**
	(−2.46)	(−2.53)	(−2.62)	(−2.69)	(−2.65)	(−2.76)	(−2.89)
$DFADUM_t$	−0.1839**	−0.1839**	−0.1831**		−0.1812**	−0.1695**	−0.1691**
	(−6.84)	(−6.87)	(−7.07)		(−6.93)	(−6.39)	(−6.59)
$SkinGame_t$	0.0078**	0.0077**	0.0084**		0.0080**	0.0029	0.0032^{+}
	(3.10)	(3.03)	(3.42)		(3.23)	(1.51)	(1.74)
Risk Controls							
$\ln ATR_{t-1}$ (×100)	−1.1107*	−0.9932*	−0.8700*	−0.2741	−0.8456^{+}	−0.7942^{+}	−0.5413
	(−2.51)	(−2.26)	(−2.05)	(−0.55)	(−1.95)	(−1.94)	(−1.36)
YC_{t-3} (×100)	0.6875**	0.6572*	0.7401**	0.6989*	0.6989**	0.5887*	0.6166**
	(2.89)	(2.75)	(3.16)	(2.18)	(2.92)	(2.60)	(2.78)
$StockCrash87_t$		−0.0733**	−0.0699**	−0.0749**			−0.0667**
		(−3.02)	(−2.78)	(−3.06)			(−2.87)
NYCDef		−0.0585*	−0.0596*	−0.0584**			−0.0572*
		(−2.37)	(−2.31)	(−2.34)			(−2.36)
Lagged first differences of long-term variables							
$\Delta \ln SHADOW_{t-1}$	0.1436*	0.1439*	0.1507*	0.1530*	0.1464*	0.1554*	0.1609*
	(2.21)	(2.22)	(2.40)	(2.02)	(2.26)	(2.43)	(2.60)
$\Delta \ln SHADOW_{t-2}$	0.2277**	0.2327**	0.2091**	0.2558**	0.2096**	0.2422**	0.2227**
	(3.58)	(3.67)	(3.38)	(3.33)	(3.35)	(3.91)	(3.67)
$\Delta \ln RRTAX_{t-1}$	−0.0151	−0.0155^{+}	−0.0165^{+}	−0.0213	−0.0157^{+}	−0.0145	−0.0150^{+}
	(−1.61)	(−1.65)	(−1.81)	(−0.99)	(−1.72)	(−1.56)	(−1.69)
$\Delta \ln RRTAX_{t-2}$	0.0043	0.0053	0.0027	−0.0092	0.0030	0.0047	0.0037
	(0.47)	(0.57)	(0.30)	(−0.41)	(0.33)	(052)	(0.42)
Lagged First Differences of Long-Term Variables							
$\Delta \ln RPIT_{t-1}$	0.0100	−0.0236	−0.0343	−0.0641	−0.0192		
	(0.04)	(−0.10)	(−0.14)	(−0.25)	(−0.08)		
$\Delta \ln RPIT_{t-2}$	−0.0154	0.0299	0.0992	0.0863	0.1123		
	(0.05)	(0.11)	(0.37)	(0.29)	(0.41)		
$\Delta MMAdvantage_{t-1}$					−0.0063		
					(−0.25)		
$\Delta MMAdvantage_{t-2}$					0.0195		
					(1.09)		
$\Delta CapDift_{t-1}$	−0.0022	−0.0023	−0.0020	0.0035	−0.0026	−0.0034	−0.0040
	(−0.29)	(−0.30)	(−0.28)	(0.36)	(−0.35)	(−0.46)	(−0.56)
$\Delta CapDif_{t-2}$	0.0039	0.0037	0.0052	0.0142	0.0052	0.0028	0.0031
	(0.53)	(0.51)	(0.74)	(1.48)	(0.73)	(0.39)	(0.45)
Summary Stats.							
Adjusted R^2	.4901	.4942	.5268	.3527	.5212	.5022	.5330
S.E.	0.0240	0.0239	0.0231	0.0234	0.0233	0.0237	0.0230
VECLM(1)	8.19	9.71	6.17	12.96	11.09	4.02	5.85

(*continued on next page*)

Table 3 (*continued*)

	Omits *DCON* and event risks	Adds Credit Controls	Adds Event Risks	Pre-Crisis Model 3	*MMAdv.* added to Model 3	Long-Run Time Trend Replaces Info. Costs	
Sample: Variable	63:1–13:3 Model 1	63:1–13:3 Model 2	63:1–13:3 Model 3	63:1–06:4 Model 4	63:1–13:3 Model 5	63:1–13:3 Model 6	63:1–13:3 Model 7
VECLM(2)	10.93	11.28	10.54	8.54	15.46	5.13	4.26
VECLM(4)	18.28	17.70	22.32	24.89	24.48	6.71	11.75
VECLM(6)	13.07	12.98	10.86	19.72	22.38	7.50	5.71

Additional Unit Root Tests for Table 2 (1962:q1–2013:q3)

	Level (SIC lag in parentheses)	5% Critical level for lag	1% Critical level for lag
ln*SHADOWGDP*	−0.720312 (2)	−3.431576	−4.002786
∆ln*SHADOWGDP*	−6.553962** (7)	−3.431576	−4.002786

Notes: +, *, and ** denotes significacet at the 90%, 95%, and 99% level, respectively. *t*-Statistics are in parentheses. A lag length of 5 minimized the AIC in models 1–4, and yielded unique, significant vectors allowing time trends in the variables and clean residuals. A lag length of 5 minimized the AIC in models 5–7, and yielded unique, significant vectors allowing time trends in the variables, a time trend in the vector, and clean residuals. Lag lengths for unit root tests are based on the SIC and all included a constant and a trend. Coefficients on lags of difference terms longer than $t-2$ are omitted to conserve space.

exogenous to the shadow share, allowing only long-run feedback from the shadow share onto the regulatory capital arbitrage variable. Long-run coefficient estimates and the short-run results are very similar across models 3–6, indicating another level of robustness to the findings.

Finally, model 7 re-estimates model 4 by omitting the yield curve and corporate bond spread variables. A longer lag length of 6 quarters was needed to obtain mixed evidence for a significant and unique cointegrating vector, which had similarly signed and significant estimated long-run coefficients with magnitudes generally near those of model 1. Nevertheless, model 7 has a notably lower degree of fit than does model 1, with a much smaller corrected R-square (.28 versus .34) and a higher standard error (.0211 versus .0202). The contrast is starker comparing models 7 and 3 (R-squares of .28 versus .46 and standard errors of .0211 versus .0182, respectively). The differences between models 7 and 1 highlight the importance of pro-cyclicality and general liquidity shock effects on the relative size of shadow banking, while the additional differences between models 3 and 1 illustrate the large impact of event risks.

Using the estimates from the cointegrating vector in the preferred model 3, one can construct an implied equilibrium share of security-funded lending. As shown in Fig. 4, the equilibrium series implied by model 3 lines up well with the actual log share and tends to slightly lead it, consistent with the sign of the t-1 lagged error-correction term. Since the estimates of the long-run cointegrating relationships are similar across models 1–4, the equilibrium levels would be similar had model 1, 2, or 4 been used. Models 5–7 also yield similar results.

5. Additional robustness checks

In addition to assessing the robustness of the shadow bank share models to different sets of short-term controls and sample periods, two other aspects of robustness are assessed. The first is whether the real information cost variable is picking up information about the shadow share beyond that of a simple a time trend. Table 2 reports an abbreviated set of results from an additional set of shadow bank share models. The first and second models in this table repeat results from the preferred model (Number 3) in Table 1 and its more parsimonious version, Model 1. In Table 2, Models 3 and 4 are respective variants of these models that drop the real information cost variable in the long-run vector (and the associated lagged first differences of it when estimating the short-run model of changes in shadow share) and add a time trend to the long-run portion of the model, the cointegrating vector. The model fits of the short-run portions of the latter two "time trend" models are smaller (corrected *R*-squares are 0.04–0.06 smaller) and the estimated speeds of error-correction are 4–7% points slower than those of the corresponding models that include information costs. This largely reflects the loss of marginal information about the long-run shadow bank share arising from replacing real information costs with a time trend. Particularly encouraging is that the signs and statistical significance of the other long-run variables (relative capital requirements, the reserve requirement tax, and regulations outlining the legality of money market funds and bank MMDA accounts) are unaffected, reflecting the underlying robustness of the specifications reported in Table 1.

An alternative to modeling the shadow bank share is to model a more absolute gauge of shadow credit use. One such natural gauge is the ratio of shadow credit borrowed by the nonfinancial corporate sector relative to that sector's output. Collapsing debt and output into a ratio shrinks the size of the cointegrating vector, making it more practically feasible to identify a single, statistically significant vector. The disadvantage of this alternative approach is that the specification of this sector's use of one type of credit might omit a key variable that affects it and nonshadow credit use, but not so much the relative use of the two types of credit. Consequently, modeling the ratio of shadow credit to GDP might be more prone to omitted variable bias than modeling the relative share of total nonfinancial corporate credit. Recognizing this potential shortcoming, the ratio of shadow debt of this sector to sectoral output (*SHADGDP*) is modeled.

Table 3 reports results from models that correspond to models 1–4 in Table 1, except *SHADGDP* replaces *SHADOW* and the money fund advantage variable (*MMAdvantage*) is dropped because it was insignificant. To illustrate the last point, Model 5 in Table 3 corresponds to Model 3 except that it includes *MMAdvantage*, which is insignificant in the long-run vector. The money fund variable's changing significance may reflect similarly timed effects of large, overall alterations in the tax incentives for corporate debt finance arising from adjustments in the impact of taxation interacted with highly variable inflation and interest rates along with modification of corporate tax rates and depreciation schedules in the 1970s through early 1980s. These hard-to-track overall tax incentives for using corporate debt could have altered the use of debt that plausibly might have affected debt-to-output ratios with little effect on the composition of shadow versus nonshadow credit. The potential for omitted variable bias in the *SHADGDP* models in Table 3 is suggested by less highly significant test statistics for cointegration, their higher standard errors (roughly 30% higher) and much slower speeds of adjustment (about 8% versus 26%) compared to the corresponding models of shadow bank credit share in Table 1. Nevertheless, unique, significant vectors were identified for each model, with the other long-run variables remaining significant with the expected signs. In this sense, the main results from modeling the shadow share with respect to the qualitative long-run effects of time-varying regulatory capital arbitrage, reserve requirement taxes, and real information costs hold up in models of shadow debt-to-output ratios. In general, the impact and statistical significance of short-run variables was similar for these models as well (including the impact effects of allowing money market mutual funds and MMDA accounts), implying robustness regarding the roles of stationary risk effects of corporate risk and Treasury yield curve premia, business cycles, and event risks in short-run movements in the use of shadow credit.

6. Conclusion

This study empirically analyzes what drove the long-run and short-run movements in the relative importance of shadow bank funding of the short-run credit of nonfinancial corporations over the past five decades. The share variable analyzed essentially captures the combined importance of the commercial paper market and nonbank financial intermediaries comprising the shadow banking system. Consistent with several strands of the regulatory arbitrage literature, the long-run equilibrium share is negatively related to information costs and positively related to the absolute burden of bank reserve requirements and the relative burden of capital requirements on commercial bank credit versus shadow bank credit. Also in line with the shadow banking and money demand literature, the shadow bank share was also affected by the introduction of innovations, such as money funds, and deregulatory steps, such as the introduction of MMDAs.

In the short-run, the shadow bank-funded share not only fell when short-run liquidity premia were high, but also when term premia reflected expectations of an worsening economy, or event risks occurred in security markets. In addition, the share rose when deposit rate ceilings were more binding or short-run regulatory changes favored nonbank relative to bank finance. The former set of findings is consistent with the view that shadow banking is pro-cyclical and vulnerable to liquidity shocks, as shown in Adrian and Shin (2009a, 2009b, 2010), Brunnermeier and Sannikov (2013), Geanakoplos (2010), Gennaioli et al. (2013), and Gorton and Metrick (2012). From a longer, more historical perspective, these results are also consistent with Bernanke (1983), pre-World War II studies of Kimmel (1939) and Young (1932), and related studies (Duca, 2013a,b) that find that during the Great Depression, the provision of credit shifted toward debt whose funding sources were less vulnerable to liquidity shocks. The qualitative findings for short-run and long-run movements virtually all held up when evaluated using less well-fitting models of shadow debt-to-output ratios.

The results of the current study have two general policy implications. First, the evidence indicates that shadow banking is very vulnerable to liquidity shocks and is very pro-cyclical, raising issues for financial and macroeconomic stability. Because DFA has made it more difficult for the Federal Reserve to quickly stabilize financial markets with interventions such as buying commercial paper, these results support arguments favoring reform of the money market mutual fund industry to make it more resilient to liquidity and other financial shocks (e.g., McCabe et al., 2013; Rosengren (2014)). Second, by imposing skin-in-the-game risk exposures to securitized assets and by applying stress tests to systemically important banks and nonbanks, DFA helped level the regulatory playing field between commercial and shadow bank credit, limiting one aspect of regulatory arbitrage while tightening financial regulation.[20] In this respect, DFA has addressed one of the earlier shortcomings of the Basel I accords. In doing so, DFA induced a retrenchment in the relative size of the shadow banking system's role in providing short-run business credit, thereby helping improve financial stability (Luck and Schempp, 2014).

From a broader perspective, the findings illustrate the need to synthesize roles of information costs, financial regulation, innovation, and risk when analyzing how the relative use of traditional deposit funded loans and nontraditional sources of credit evolved, as stressed in various strands of the money and banking literature (e.g., Adrian and Shin (2009a,b), Edwards and Mishkin (1995), Kanatas and Greenbaum (1982), Kashyap et al. (1993), Pennacchi (1988), *inter alia*). By developing a financial architecture model of shadow banking's role in short-term business finance and using it to empirically assess the influence of different factors over the past half-century, the current study helps address one of the gaps in the shadow banking literature and hopefully will indirectly contribute to future studies in other ways as well.

[20] This statement is not an overall assessment or evaluation of DFA, which is beyond the scope of this study.

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