How Capital Regulation and Other Factors Drive the Role of Shadow Banking in Funding Short-Term Business Credit

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This paper analyzes how capital regulation, risk, and other factors altered the relative use of shadow banking system-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, the economic outlook improved, or risk premia declined, and fell when event risks disrupted financial markets.

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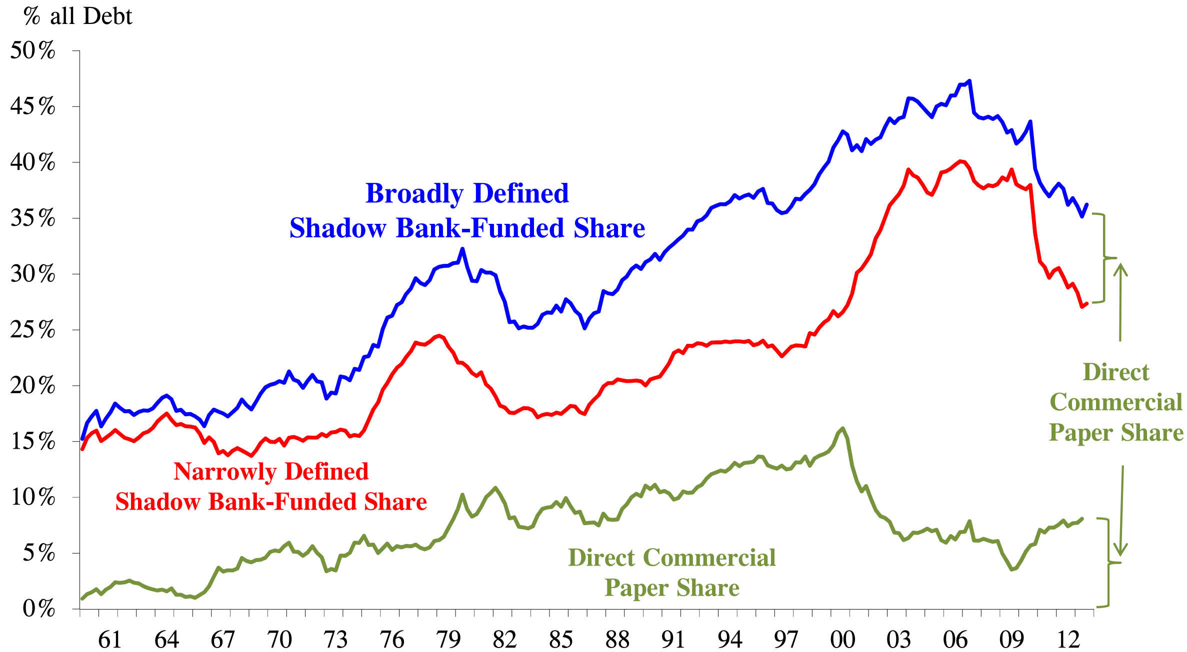
I. Introduction

The relative importance of the "shadow banking system" is generally thought to have increased in the decades preceding the 2007-09 financial crisis in the U.S. before subsiding following the crisis amid efforts to reform the financial system. For example, in terms of funding the short-term business credit of nonfinancial corporations, the use of credit funded by securities markets had risen relative to that directly funded by banks—e.g., nonbank loans funded with uninsured debt, bank loans securitized and sold into the financial markets, and commercial paper directly issued by nonfinancial corporations typically bought by money funds. As Figure 1 shows, the share of short-term debt of nonfinancial corporations funded by commercial paper and nonbank loans has roughly doubled since the late 1960s, and netting out commercial paper directly issued by nonfinancial corporations, there have been large shifts in the share of debt intermediated by nonbank financial firms.[1] This is important because 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), and Gorton and Metrick (2012), *inter alia*. 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. These 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.

Disparate strands of the literature imply that the extent to which business finance is funded through securities markets has evolved, reflecting the long-run effects of regulatory

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

Figure 1: The Relative Importance of the Shadow Banking System as Tracked by the Security-Funded Share of Short-Run Nonfinancial Business Credit



arbitrage and financial innovation, as well as short-run financial market shocks. Combining these insights could provide a more cohesive framework for understanding both the long-run evolution and short-run variation in shadow banking's relative importance. Such financial architecture models could 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. Filling a gap in the literature, this paper empirically models the relative use of short-run nonfinancial corporate debt funded by securities markets, in both the short and long runs, using a half-century of data.

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 over the past several decades. 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.

II. Literature Review: What Is and What Drives Shadow Banking?

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

II.A. Defining Shadow Banking

Attempts to define and measure shadow banking take several approaches. For example, the Financial Stability Board (2012, p. 3) defines shadow banking as, "credit intermediation involving entities and activities outside the regular banking system," which the document later clarifies as inclusive of securitization and nonbank lenders. From this broad viewpoint, 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 more detail how shadow banks address several apparent unmet needs of financial markets. They note that the liabilities that shadow banks create help address the need for collateral in financial markets, and that shadow banks help address some credit demands unmet by commercial banks. An alternative definition is offered by Claessens and Ratnovski (2014), who propose defining shadow banking as, "all financial activities, except traditional banking, which require a private or public backstop to operate." Another aspect of shadow banking is that the shadow and more conventional bank activities are often intertwined (see Claessens, et al. (2012) and Jackson (2013)), making it difficult to track shadow banking by simply looking at a simple disaggregation of credit or liabilities by the type of financial intermediary.

IIB. 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, and 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, Gertler, and Gilchrist, 1996; Duca, 2013b; Jaffee and Russell, 1976; Keeton, 1979; Lang and Nakamura, 1995; and 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 vulnerability of financial firms and the financial system to liquidity risk (Adrian and Shin, 2009a, 2009b, 2010). 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 percent 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.[2]

Recent experience suggests that surges 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), and 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 percent during the 25 months between July 1930 and August 1932, but by a less dramatic 44 percent between July 2007 and August 2009. In contrast to the 1930s, the Federal Reserve used several asset purchase programs to limit surges in risk premia on high-grade commercial paper and residential mortgage-backed securities. Some of the smaller decline in commercial paper in the recent crisis also reflects the stronger macroeconomic policy response relative to the Great Depression.

Despite the limited literature on policy actions intended to counter the Great Recession, there has been little econometric analysis of what factors contributed to the rise of shadow banking 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

[2] BAs are time drafts drawn on banks to finance the shipment or storage of goods. Banks guarantee payment to BA owners, making BAs tradable as investors know more about banks than goods buyers. The latter receive credit to pay sellers from banks, which fund credits by selling BAs. Goods collateralize BAs for banks. This contrasts with the unbacked commercial paper of the Great Depression era and more recent asset-backed commercial paper that is backed by paper assets whose values fell after 2006. Using ratios of BAs and commercial paper abstracts from other factors.

of data, the role of several potential factors—not just the latest fad—are assessed, and the sample is extensive enough to disentangle short- from long-term effects. By not being limited to the Great Moderation era, the time series analysis draws from experience spanning different regulatory regimes, which may provide more perspective on recent attempts at financial reform.

This study assesses how the relative importance of the shadow banking system is affected by short- and long-run factors stemming from regulatory burdens and information costs, drawing on insights from Kashyap, Wilcox, and Stein (1993) on the role of commercial paper in short-run business finance and Oliner and Rudebusch (1995) regarding the broad-based rather than narrow-based (bank) view of the credit channel of monetary policy. The models use data from the Federal Reserve's Financial Accounts of the U.S., covering a broad range of credit funded with commercial paper and other market debt. The relative use of credit funded by commercial paper (e.g., commercial paper and nonbank loans funded by securities issued by finance companies and asset-backed securities (ABS) lenders) versus bank-intermediated credit reflects the advantages of avoiding bank regulations (e.g., reserve and capital requirements, as in 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, and Kashyap, Wilcox, and Stein, 1993); (3) the theoretical and empirical literature on the securitization of bank loans (e.g., Pennacchi, 1988); and (4) a 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), and 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 will allow lenders. In their model of lending funded without insured deposits, Schleifer 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.

II.C. 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 (e.g., of the changing role of shadow banks in supplying new types of liabilities to address a growing need for collateral) is left to future research. The availability of consistently defined time series data prevents testing more detailed hypotheses (e.g., some issues regarding how the credit needs are met of borrowers with soft versus hard information—see Ratnovski, 2014). Nevertheless, some roles played by commercial banks in shadow banking are addressed—for example, treating securitized C&I loans as a form of shadow banking.

III. Model Specification and Data

IIIA. 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 nonbank financial intermediaries. First, much of this 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 (Figure 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 subsequently 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 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, so there is much less need to model volatile business fixed investment 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.[3] 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.

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

[3] 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.

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:

$$\log(SHADOW) = \lambda_0 + \lambda_1 \log(X) + \lambda_2(Z)$$

$$\Delta\log(SHADOW)_t = \alpha_0 + \alpha_1 \log(EC)_{t-1} + \beta_i \Delta\log(SHADOW)_{t-i} + \theta_i \Delta\log(X)_{t-i} + \delta Z_t$$

$$EC \equiv \log(SHADOW) - [\lambda_0 + \lambda_1 \log(X)] \qquad (1)$$

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.

IIIB. Data and Variables

Most of the determinants of the relative use of security- or shadow bank-funded credit 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 to these more structural variables, short-run financial shocks can also be tracked. Following a description of how shadow banking is observed, the variables tracking its determinants are discussed in the order mentioned above.

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 Flow of Funds data on nonfinancial corporate debt since 1961:q4 (*Figure 1*). *SHADOW* equals the sum of directly issued commercial paper plus finance company loans plus other loans financed by asset-backed commercial paper (securitized commercial and industrial (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). 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.

Long-Run Information and Transactions Costs

In addition to regulatory arbitrage, the rise of shadow banking over recent decades partly stems erosion of banks' informational and transactions cost advantages over nonbanks, owing to improvements in technology (e.g., Edwards and Mishkin, 1995, and Mishkin, 2009), which plausibly enable borrowers to more easily provide hard information which allows them to "shop around" among traditional and shadow banks for credit (Ratnovski, 2013). Studies of the rising importance of mutual funds emphasize the role played by declining transactions costs at nonbanks, which stem from improvements in overall financial sector productivity (Duca, 2000 and 2005). To parsimoniously model the influence of general declines in information costs, which likely capture declines in transactions costs, long-run models include a measure of information technology prices. Quarterly data on the implicit price deflator for information processing equipment were applied to the overall GDP chain price deflator to construct *RPIT* (*Figure 3*), 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.

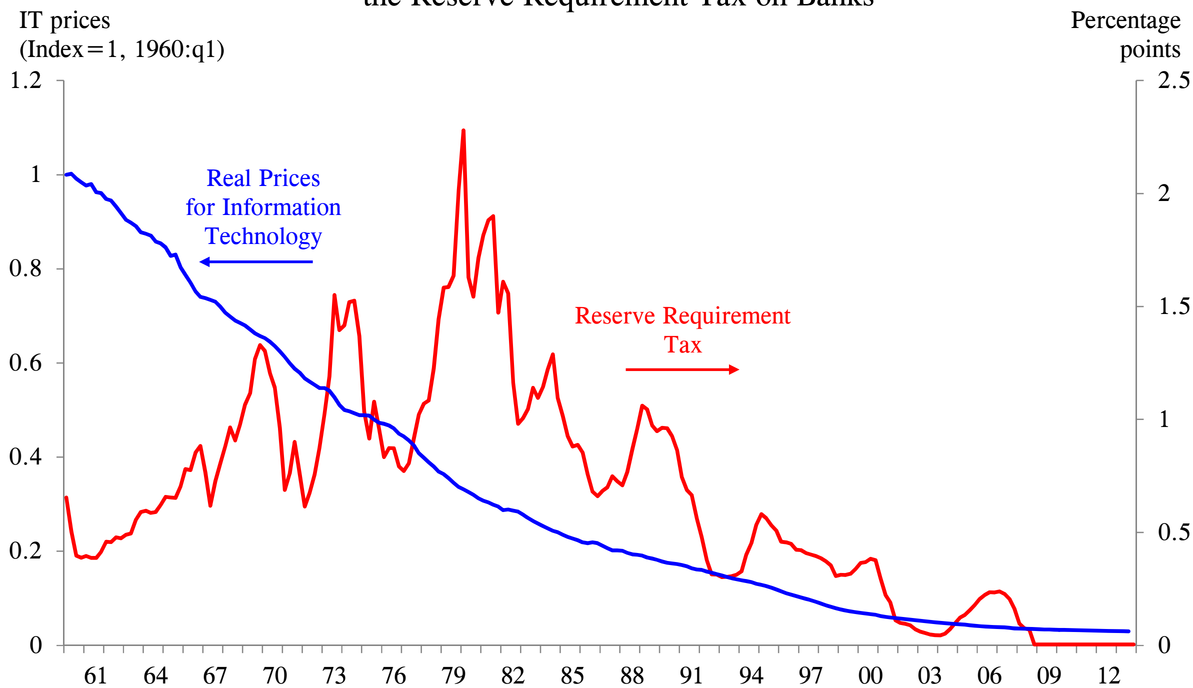
The Burden of Reserve Requirements

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; and Rosengren, 2014). The reserve requirement tax can be proxied by nominal interest rates until the Fed started paying interest on reserves, in 2008:q4. However, the three-month T-bill rate (*3monTR*) was integrated of order 2 if substantial changes in reserve requirements are not taken into account.

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 (*Figure 2*) on banks in central reserve city banks (large banks), with an adjustment for the advent of 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 the reserve requirement tax. 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 percent of sweep balances (St. Louis Federal Reserve Bank, 2010) roughly equals the maximum 10 percent marginal reserve requirement for large banks, the ratio gauging the reserve requirement tax. The reserve requirement tax equals 0.01 percent over 2008:q4 - 2011:q4 reflecting near zero short-term Treasury bill rates and the payment of similar interest on reserves.

Reflecting the combination of all of these factors, the reserve requirement burden was high in the 1970s through early 1980s, but has since fallen to record low levels following the financial crisis (*Figure 2*). Changes in the reserve requirement tax, which were an impetus for the rise of shadow banking in the 1970s and early 1980s, have tempered the growth of shadow banking, particularly since the 2007 onset of the financial crisis.

Figure 2: Real Information Technology Costs and the Reserve Requirement Tax on Banks



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, thereby encouraging banks to tighten their credit standards, consistent with the findings of Duca, Muellbauer, and Murphy (2012). One variable to track these effects on retail deposits is Duca's

(1996) measure of how much Regulation Q ceilings on retail deposit interest rates were binding until Regulation Q ceilings were lifted 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 security-funded 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).

In addition to interest rate ceilings on retail deposits, 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 of measures of the bindingness of Regulation Q on retail deposits. For this reason a separate bindingness measure for large time deposits was statistically insignificant in other runs not shown in Tables 1 or 2, as was a dummy for the lifting of deposit rate ceilings on large time deposits in 1974:q2.

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 really notable until about 1973, and check-writing features on MMMFs for households were introduced in the late spring of 1974 by Fidelity Investments. By giving investors an option to purchase a more liquid form of commercial paper, the rise of money market funds lowered the costs of funding commercial paper and other forms of open market paper relative to banks. Partly to counteract this drain on the banking system, banks were allowed to offer MMDAs starting in 1982:q4. This resulted in inflows into bank deposits from both 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, which largely 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.

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; Penacchi, 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 of the commercial banking system faced an official minimum 5 percent leverage ratio (see Wall and Peterson, 1987),[4] 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 percent between the early 1970s and again when 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 percent. 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.[5] Effectively, C&I loans held in portfolio by large and medium-sized banks faced a 5 percent minimum capital ratios before 1985 and 5.5 percent between 1985 and 1989, respectively, whereas nonbank financial intermediaries faced no regulatory minimums and many investors could purchase commercial paper with no regulatory capital requirements imposed on them. During these two respective periods, the marginal regulatory capital differential between bank and shadow bank short-term credit was arguably 5 and 5.5 percentage points, respectively.

The implementation of Basel I in 1990 raised the capital requirement on most bank loans held in portfolio from 5.5 percent to 8 percent, encouraging the rise of shadow banking by inducing more securitization.[6] 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 height of the structured finance boom of the 2000s. Partly because

[4] Small community banks faced a 6% minimum, and larger regional and money center banks faced a 5% minimum.
[5] Bank holding companies (BHCs) expanded in the late 1960s, aided by the Bank Holding Company Act of 1970, which took effect in mid-1971. 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 decline in the banking industry's aggregate capital ratio from 7 percent in the 1960s to 6 percent by the early 1970s.
[6] 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.

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, and 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 percentage points, thereby promoting the relative importance of shadow banking.

The regulatory playing field became relatively less favorable to shadow banking following the passage of the Dodd-Frank Act (DFA), which had three types of provisions relevant to modeling the shadow bank share of short-term business credit. First, the rules enacting this financial reform raised the minimum capital requirement on C&I loans held in portfolio to 10.5 percent. Second, the act required banks to hold capital against losses of up to 5 percent 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 percent 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 percent 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 percent to 5.5 percent (10.5 percent on loans minus a 5 percent reserve on securitized C&I loans). Not surprisingly, near the passage of DFA, the shadow bank share of short-term business credit underwent a sharp downward shift that has not reversed.[7]

[7] DFA toughened requirements on derivatives to improve their transparency, partly in an attempt to lower the systemic risk they create. That risk is seen as contributing to the rise of shadow banks and their role in the recent financial crisis (see Duca, et al., 2010). DFA also imposed minimum liquidity ratios on systemically important bank

This study parsimoniously tracks the shifts in capital regulatory arbitrage effects in an econometric framework with the variable *CapDif* (Figure 3), which equals the differential in minimum capital requirements for commercial bank and shadow bank credit at 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 percent minimum capital ratio before 1985 and 5.5 percent 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 percent 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 percent 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 percent during this era. And in the DFA era, *CapDif* equals 5.5 percent to reflect the narrowing of the effective regulatory capital differentials between C&I loans held in portfolio and those securitized by loan originators. Because the level of *CapDif* enters the error-correction models with a t-1 lag and the regulations it reflects were announced in advance of implementation, *CapDif* equals 5 before 1985, 5.5 up until 1989:q2, 8 between 1989:q4 and 2010:q3, and 5.5 starting in 2010:q4.[8] To control for the short-run effects of DFA and pressure on financial institutions to conform quickly with it, a DFA implementation dummy (*DFADUM*) equal to 1 in 2010:q4 was also included (the inclusion of this dummy barely affects estimated long-run coefficients while tracking an unusual outlier).

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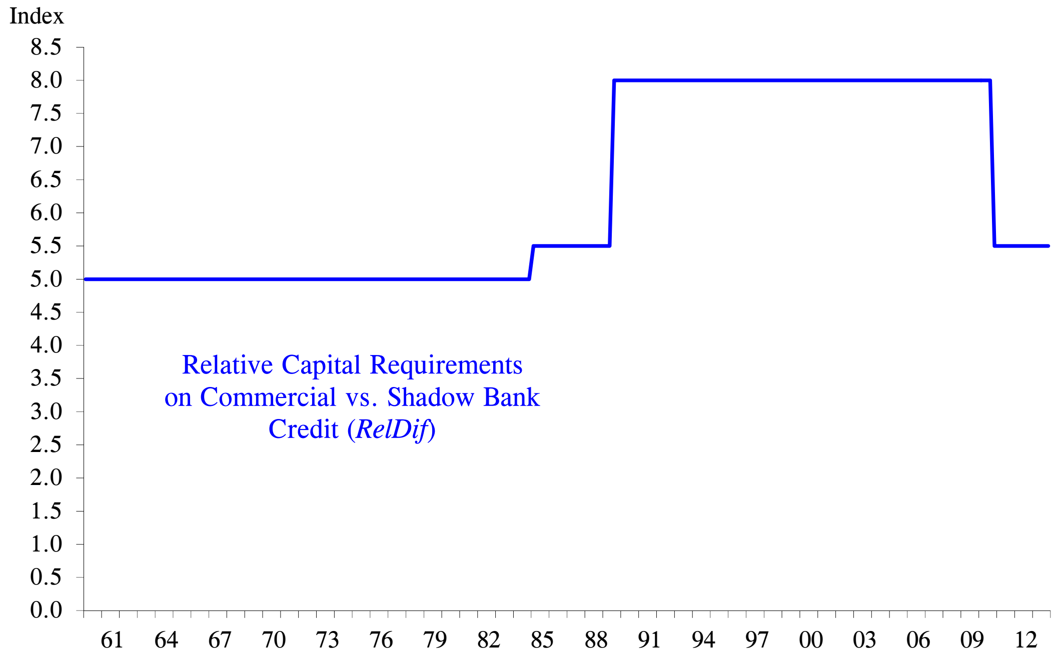
and nonbank financial firms that restrict not only their individual duration risk, but also (and perhaps more importantly) their associated systemic risks posed by asset maturity transformation (see Gorton and Metrick, 2012).

[8] 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 and was not included in the models reported in Table 1.

Tracking the Impact of Risk Premia and Procyclical Influences on Business Credit Sources

The safety net for commercial banks tends to favor them over shadow banks during 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*),[9] reflecting its usefulness as a leading economic

Figure 3: Tracking the Relative Impact of Capital Regulations on Commercial Bank Versus Shadow Bank Funding



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 premia outperformed those that replaced the one-year Treasury rate with either the federal funds rate or the three-month Treasury rate.

[9]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.

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 (2013b)). *A10TR* outperformed the spread between Baa-rated corporate and 10-year Treasury yields, perhaps reflecting the relative thinness of trading in Baa-rated firms that sometimes pose the risk of being downgraded to below investment-grade status. *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 as well as more specific shocks to commercial banks relative to other financial firms, implying an ambiguous effect on the shadow bank share.

Because liquidity spreads may not track all flights to quality, a set of dummy variables for special events affecting business finance sources were included in some regressions. Among these were a dummy, *PennCentral*, equal to 1 in the quarter when the Penn Central railroad declared bankruptcy and defaulted on its commercial paper, -1 in the next quarter when the flight to quality unwound, and 0 otherwise.[10] A similarly structured discrete variable, *StockCrash87*, equals 1 when the stock market crashed in 1987:q4. Another event risk dummy was for the near 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 discrete variable, *DBNP*, equals 1 in 2007:q4, typically seen as the start of the 2007-09 housing and financial crisis in the U.S., which was triggered on August 9 when three BNP hedge funds suspended redemptions because their subprime positions could not be priced to market values (Duca, Muellbauer, and Murphy, 2010). Of these event risk variables, three (*PennCentral*, *NYCDef*, and *DBNP*) are associated with disruptions that initially more notably affected shorter-term debt markets relevant for funding shadow banking and were not fully reflected in changes in corporate bond risk premia. The stock market crash of 1987 was a more general, albeit temporary, shock to the whole financial system as it initially raised fears that an economic depression might ensue. Because commercial banks have a more explicit and comprehensive safety net support than shadow banks, tail risk events—such as stock market crashes—could conceivably induce investors to shift the composition of shorter-term asset holdings from uninsured debt into insured bank deposits or Treasury bills to an extent not fully reflected in corporate bond risk 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.

[10] A similar dummy for the failure of the commercial bank Continental Illinois was insignificant in other runs.

IV. 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*, the reserve requirement tax, the information technology price series, regulatory shift, and relative minimum capital ratio variables.[11][12] 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 (such as those reported in the text or in footnotes) was adopted in constructing the preferred model, number 3. In presenting

[11] Unit root test statistics are provided at the bottom of Table 1.

[12] Unfortunately, owing to data availability limitations over a 50 year period, there is little that can be done to sharply distinguish between supply and demand factors beyond what is implicit in the modeling strategy. By focusing on modeling the shadow bank share rather than the level of shadow bank credit, the model largely abstracts from demand factors that plausibly affect the numerator and denominator of the market share variable in the same direction. Additionally, long-run drivers of the shadow share are very arguably supply-side factors—it is very plausible to see capital and reserve requirement regulatory arbitrage effects (regulations on money funds versus MMDA regulations)—as affecting the relative supply of shadow versus non-shadow bank 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 in securities markets. 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 the noncorporate, nonfinancial business sector (tending to include much smaller-sized private companies) runs counter to this product market channel.

the results, Table 1 adopts an ordering of models to illustrate the impact on a baseline model of adding short-run factors in building up to the preferred model, number 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.

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 for use in a second-step VAR in first differences for modeling short-run movements (log first differences). For each model, unique and statistically significant cointegrating vectors are estimated, allowing 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..

In models 1-4, the error-correction term was only significant in models of the change in the shadow share and regulatory arbitrage, having two interesting and sensible implications. First, this indicates 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 affect information costs, the reserve requirement tax, and regulations about MMMFs and MMDAs, whereas long-run movements in the latter three variables Granger cause the shadow share in a long-run sense. This is plausible.

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 much 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 the Dodd-Frank Act 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 one would expect. In every model, the estimated speeds of adjustment are similar, implying that roughly 23 to 27 percent of disequilibria are eliminated on average per quarter. This speed is sensible given the large structural shifts in the security market-funded share of business credit 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.

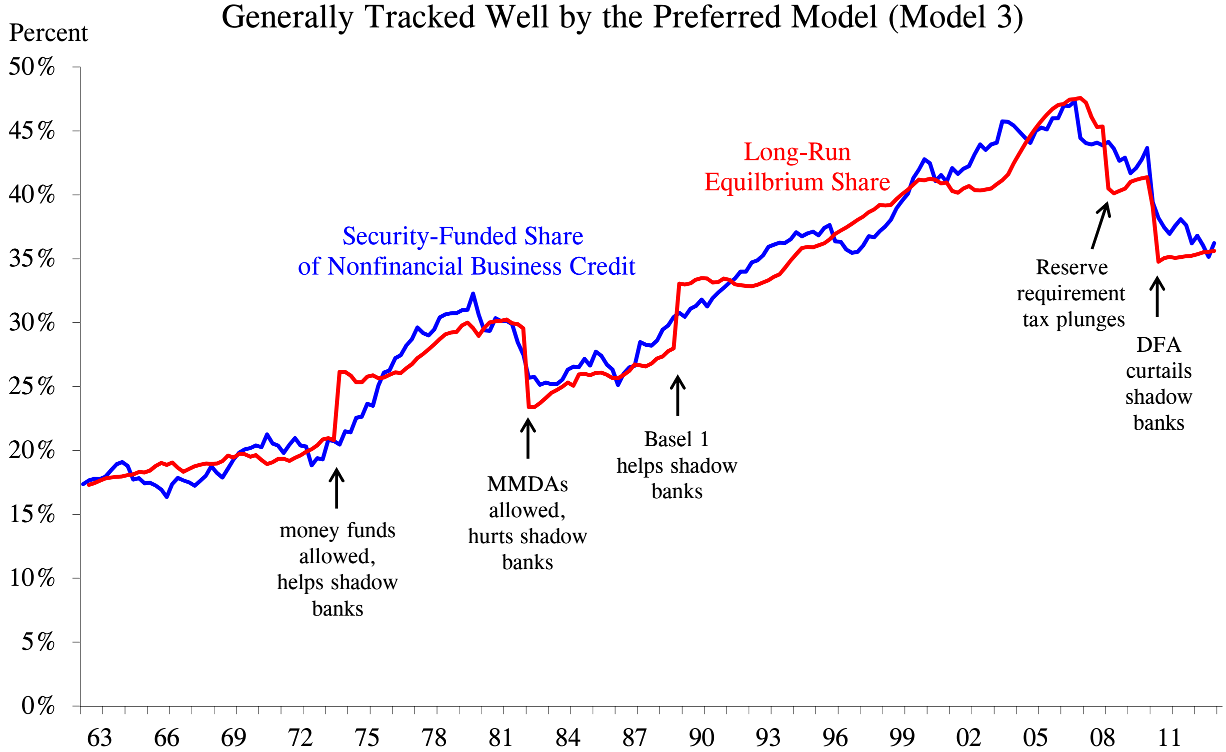
A challenge to incorporating regulatory regimes into time series models is that the coefficient estimates may not be robust to the samples used. While some of this is inevitable given the nature of regime shifts, it is important to assess the reliability of coefficient estimates. Balancing these two 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). Ending the sample in 2006:q4 avoids including observations near the August 2007 shock to financial markets, the rescue purchase of Bear Stearns by JPMorgan Chase in the spring of 2008; and the failure of Lehman in September 2008. 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.

As another robustness check, models 5 and 6 use the same set of short-run controls and sample as model 4, but are estimated imposing the restriction that information costs, the reserve requirement tax, and regulations affecting money funds and MMDAs are weakly exogenous to the shadow share, allowing only long-run feedback from the shadow share onto the regulatory capital arbitrage variable. The short-run results are very similar across models 3, 5, and 6.

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 Figure 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.

Figure 4: Shadow Bank Share of Nonfinancial Business Credit
Generally Tracked Well by the Preferred Model (Model 3)



V. 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 to 0.06 smaller) and the estimated speeds of error-correction are 4 to 7 percentage 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 natural such 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 percent versus 26 percent) 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.

VI. 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 that comprise 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 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 market mutual 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, term premia reflected expectations of an improving economy, or event risks occurred in security markets, but also 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 procyclical and vulnerable to liquidity shocks, as shown in Adrian and Shin (2009a, 2009b, 2010), Brunnermeier and Sannikov (2013), Geankoplos (2010), 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, 2013b) that find that during the Great Depression, the provision of credit shifted towards 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 against liquidity and other financial shocks (e.g., McCabe, *et al.* (2013) and 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.[13] In this respect, DFA has addressed one of the earlier shortcomings of the Basel I accords. In doing so, it has induced a retrenchment in the relative size of the shadow banking system's participation in providing short-run business credit.

From a broader perspective, the findings illustrate the need to synthesize roles for information costs, financial regulation, innovation, and risk when analyzing the evolution of the relative use of traditional deposit funded loans and nontraditional sources of credit 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, Wilcox, and Stein (1993), and 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 as well.

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

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Table 1: Quarterly Error-Correction Models of the Change in the Shadow Bank (Security-Funded) Share of NonFinancial Corporate Short-Term Debt

A. Long-Run Equilibrium Relationships: $\ln \boldsymbol{SHADOW} = \lambda_0 + \lambda_1 \ln \boldsymbol{RRTAX} + \lambda_2 \ln \boldsymbol{RPIT} + \lambda_3 \boldsymbol{MMadv} + \lambda_2 \boldsymbol{CapDif}$

					Long-Run Feedback Only Between *SHADOW* & *CapDif*		
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**
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)
MMAdvan-	0.2108**	0.2119**	0.2211**	0.2215**	0.2210**	0.2210**	0.2030**
$tage_{t-1}$	(10.09)	(10.01)	(12.25)	(11.74)	(12.14)	(11.71)	(7.22)
$RelDif_{t-1}$	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.)	28.23645	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					4.1276	0.6922	
exogeneity					(insignificant)	(insignificant)	

B. Short-Run Equilibrium Relationships

$$\Delta \ln SHADOW_t = \alpha_0 + \alpha_1 \log(EC)_{t-1} + \beta_i \Delta \log(SHADOW)_{t-i} + \theta_i \Delta \log(X)_{t-i} + \delta Y_t$$

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
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							
$REGQ_{t-2}$	1.4550**	1.4031**	1.3708**	1.3476**	1.3553**	1.3426**	0.7360*
(x100)	(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)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
			Regulatory Controls (continued)				
$DMMMF_{t-1}$	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				
$lnATR_{t-1}$ (x100)	-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} (x100)	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)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
			Lagged First Differences of Long-Term Variables (continued)				
$\Delta\ln RPIT_{t-1}$	-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)
$\Delta MMAdavantage_{t-1}$	-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)
$\Delta MMAdavantage_{t-2}$	-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)
$\Delta RelCapital_{t-1}$	-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)
$\Delta RelCapital_{t-2}$	-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)
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
$\Delta\ln SHADOW$	-5.174103^{**} (7)	-3.431682	-4.003005
$\ln RRTAX$	-1.192915 (0)	-3.432005	-4.003675
$\Delta\ln RRTAX$	-12.32873^{**} (0)	-3.432005	-4.003675
$\ln RPIT$	1.795024 (1)	-3.432005	-4.003675
$\Delta\ln RPIT$	-7.298104^{**} (0)	-3.432005	-4.003675

Notes: $^{+}$, *, and ** denotes significancet 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.

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

A. Long-Run Equilibrium Relationships: $\ln \boldsymbol{SHADOW} = \lambda_0 + \lambda_1 \ln \boldsymbol{RRTAX} + \lambda_2 \ln \boldsymbol{RPIT}$ ***or TIME*** $+ \lambda_3 \boldsymbol{MMadv} + \lambda_2 \boldsymbol{CapDif}$

			Long-Run Time Trend Replaces Info. Costs	
Sample:	63:1-13:3	63:1-13:3	63:1-13:3	63:1-13:3
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
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)
$RelDif_{t-1}$	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

$$\Delta \ln SHADOW_t = \alpha_0 + \alpha_1 \log(EC)_{t-1} + \beta_i \Delta \log(SHADOW)_{t-i} + \theta_i \Delta \log(X)_{t-i} + \delta Y_t$$

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
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+

Table 3: Quarterly Error-Correction Models of the Change in the NonFinancial Corporate Shadow Bank (Security-Funded) Debt Relative to Output

A. Long-Run Equilibrium Relationships: ln***SHADOWGDP*** **=** $\lambda_0 + \lambda_1$ln***RRTAX***+ $\lambda_2$ln***RPIT***+ λ_3***MMadv***+ λ_2***CapDif***

						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**
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**	-0.00967**
Time mod.5-7	(-9.60)	(-9.49)	(-10.32)	(-10.35)	(-9.48)	(12.07)	(-13.00)
MMAdvan-					0.0014		
$tage_{t-1}$					(0.02)		
$RelDif_{t-1}$	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

$$\Delta \ln SHADOWGDP_t = \alpha_0 + \alpha_1 \log(EC)_{t-1} + \beta_i \Delta \log(SHADOWGDP)_{t-i} + \theta_i \Delta \log(X)_{t-i} + \delta Y_t$$

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
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							
$REGQ_{t-1}$	0.8651*	0.7979*	0.9666**	0.8181*	0.8946*	0.7852*	0.9140*
(x100)	(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)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
				Regulatory Controls (continued)			
$DMMMF_t$	0.0647* (2.52)	0.0656* (2.57)	0.0661** (2.67)	0.0676* (2.59)	0.0730* (2.03)	0.0586* (2.38)	0.0560* (2.35)
$DMMDA_t$	-0.0628* (-2.46)	-0.0643* (-2.53)	-0.0645** (-2.62)	-0.0700** (-2.69)	-0.0657** (-2.65)	-0.0671** (-2.76)	-0.0678** (-2.89)
$DFADUM_t$	-0.1839** (-6.84)	-0.1839** (-6.87)	-0.1831** (-7.07)		-0.1812** (-6.93)	-0.1695** (-6.39)	-0.1691** (-6.59)
$SkinGame_t$	0.0078** (3.10)	0.0077** (3.03)	0.0084** (3.42)		0.0080** (3.23)	0.0029 (1.51)	0.0032+ (1.74)
Risk Controls							
$lnATR_{t-1}$ (x100)	-1.1107* (-2.51)	-0.9932* (-2.26)	-0.8700* (-2.05)	-0.2741 (-0.55)	-0.8456+ (-1.95)	-0.7942+ (-1.94)	-0.5413 (-1.36)
YC_{t-3} (x100)	0.6875** (2.89)	0.6572* (2.75)	0.7401** (3.16)	0.6989* (2.18)	0.6989** (2.92)	0.5887* (2.60)	0.6166** (2.78)
$StockCrash87_t$			-0.0733** (-3.02)	-0.0699** (-2.78)	-0.0749** (-3.06)		-0.0667** (-2.87)
NYCDef			-0.0585* (-2.37)	-0.0596* (-2.31)	-0.0584** (-2.34)		-0.0572* (-2.36)
			Lagged First Differences of Long-Term Variables				
$\Delta \ln SHADOW_{t-1}$	0.1436* (2.21)	0.1439* (2.22)	0.1507* (2.40)	0.1530* (2.02)	0.1464* (2.26)	0.1554* (2.43)	0.1609* (2.60)
$\Delta \ln SHADOW_{t-2}$	0.2277** (3.58)	0.2327** (3.67)	0.2091** (3.38)	0.2558** (3.33)	0.2096** (3.35)	0.2422** (3.91)	0.2227** (3.67)
$\Delta \ln RRTAX_{t-1}$	-0.0151 (-1.61)	-0.0155+ (-1.65)	-0.0165+ (-1.81)	-0.0213 (-0.99)	-0.0157+ (-1.72)	-0.0145 (-1.56)	-0.0150+ (-1.69)
$\Delta \ln RRTAX_{t-2}$	0.0043 (0.47)	0.0053 (0.57)	0.0027 (0.30)	-0.0092 (-0.41)	0.0030 (0.33)	0.0047 (052)	0.0037 (0.42)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
			Lagged First Differences of Long-Term Variables (continued)				
$\Delta \ln RPIT_{t-1}$	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)		
$\Delta MMAdavantage_{t-1}$					-0.0063		
					(-0.25)		
$\Delta MMAdavantage_{t-2}$					0.0195		
					(1.09)		
$\Delta RelCapital_{t-1}$	-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)
$\Delta RelCapital_{t-2}$	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
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
$\Delta \ln SHADOWGDP$	-6.553962^{**} (7)	-3.431576	-4.002786

Notes: $^{+}$, *, and ** denotes significancet 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.