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Intra-Financial Lending, Credit, and Capital Formation *

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Abstract

This paper examines the effects of intra-financial lending – claims between financial institutions – on aggregate investment and credit to the non-financial sector in the United States. Building on Montecino, Epstein, and Levina (2014) we document a large growth in intra-financial assets beginning in the early 1980s. Using a vector autoregression model, we find that intra-financial lending is negatively related to gross capital formation and present evidence that this operates through a credit channel. However, we also find evidence of a structural break around the year 2000. Rolling impulse response functions suggest the presence of two alternative regimes over the post-war period: a "capital diversion" regime in which credit to the non-financial sector and intra-financial lending are substitutes, as well as a financial bubble regime in which credit and intra-financial lending are complements. In the latter case, credit to the non-financial sector and intra-financial lending appear to feed each other in an unsustainable bubble process. In neither case do we find macroeconomic evidence in support of the financial efficiency view that increased intra-financial lending reflect financial innovations associated with more efficient risk bearing, liquidity provision, and credit allocation.

JEL classification: G01, G10, G20

Keywords: Finance, Intra-financial lending, Financial crisis, Rolling VAR, Block bootstrap

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1 Introduction

The last three decades have witnessed a vast expansion of the size of the financial sector in the United States. The growth of the financial sector is remarkable whether one measures it as a share of GDP, the stock of financial assets, or in terms of employment (Epstein and Crotty [16]; Greenwood and Scharfstein [19]). But the changes in the US financial sector are not only quantitative in nature: the growth of finance has been accompanied by major qualitative changes in the structure of finance and in a proliferation of complex new financial instruments. As we show in Montecino, Epstein and Levina [25], a significant part of this explosive growth in finance has been associated with a large increase in intra-financial lending, that is, the lending of financial institutions to each other, rather than lending to the real economy. This large growth in financial activity in general, and the massive increase in intra-financial lending in particular, raises several important questions about the impacts of this growth.

Has this explosion in financial activity been socially beneficial? Has it been accompanied by a behavioral change in the conduct and function of finance? And what macroeconomic consequences, if any, have these changes had? Adair Turner [32] famously remarked that "there is no clear evidence that the growth in the scale and complexity of the financial system in the rich developed world over the last 20 to 30 years has driven increased growth or stability, and it is possible for financial activity to extract rents from the real economy rather than to deliver economic value." Similarly, Phillipon [27], using an extended version of the neoclassical growth model with an explicit financial sector, finds that the US financial system has become less efficient over the last several decades. Epstein and Crotty [16], utilizing different measures than Phillipon, suggest that the rent extraction by finance for every dollar contribution of finance toward productive investment has risen significantly in the US during the post-war era. Greenwood and Scharfstein [19] also raise questions about the social vs. private benefits of the recent growth of financial activities in the US.

Arcand, Berkes, and Panizza [3] present empirical panel data evidence that there is indeed such a thing as "too much finance." Their estimates suggest that the relationship between real GDP growth and credit to the private sector is non-linear: once credit exceeds a critical threshold of 100 percent of GDP its marginal effect on growth becomes negative. And most importantly, this negative effect does not operate through a higher likelihood of experiencing financial crises. More generally, Sturn and Epstein [30] present empirical evidence suggesting that the oft-found positive connection between the growth of finance and economic growth might be simply due to business cycle impacts.

A related literature focuses on the financial stability implications of such increases in intra-financial flows. As a number of economists have argued, the Great Financial Crisis of 2007-2008 was precipitated by a "run on the financial sector by the financial sector" (DArista [11]; Gorton and Metric [18]). Greenwood and Scharfstein [19], Poszar et. al. [28] and Bernardin [4] note the lengthening of the intermediation chain associated with modern finance and question whether these might lead to more fragile financial structures.[1],

[1]Early work (see for example, the seminal paper by Allen and Gale [2]) found that financial systems with more complete network structures (i.e. a greater degree of "interconnectedness") were more robust than less interconnected financial systems. However, more recent contributions have questioned the result that greater financial interconnectedness promotes stability and

Similarly, in recent years there has been a growing interest in the complexity and network structure of the financial system and how these pertain to systemic risk. For instance, Shin [29] suggested that greater interconnectedness in the form of securitization has had perverse effects, leading to the concentration rather than the dispersal of risk. Janet Yellen [34], Chair of the Board of Governors of the Federal Reserve, noted that "interconnections among financial intermediaries are not an unalloyed good. Complex interactions among market actors may serve to amplify existing market frictions, information asymmetries, or other externalities."

Despite a growing recognition that lending between financial institutions could have potentially important macroeconomic consequences, few studies have attempted to estimate its magnitude. A notable exception is Bhatia and Bayoumi [6], who showed using data from the Flow of Funds that "the financial sectors vast expansion over 1980 – 2007 primarily reflected an explosion of claims between financial intermediaries." Montecino, Epstein and Levina [25] extended Bhatia and Bayoumi's results and constructed comprehensive measures of intra-financial assets. A number of stylized facts emerged from this analysis. Intra-financial assets (IFA) as a share of total financial sector assets appear to have nearly tripled since the 1950s. The IFA share was mostly stable around 10 percent from 1950 to the mid-1970s. However, it subsequently grew dramatically beginning in the 1980s and accelerated during the 1990s until the burst of the dot com bubble in 2001. Furthermore, the expansion of intra-financial assets after 1980 was driven by the introduction of new financial instruments and coincides with the development of the modern money market and emergence of securitization.

Though our earlier paper examined trends in the evolution of intra-financial stocks and flows, we did not assess the impacts of these trends on the macro-economy more generally. In particular, we did not assess the degree to which these increases in intra-financial lending contributed to the financing of productive investment, or to financial stability (or instability).

In what follows we address some of these questions. In particular, we examine empirically the relationship between intra-financial lending, credit supply and aggregate fixed investment. To our knowledge, this is the first attempt to evaluate empirically the effect of greater financial sector lending to itself on the real economy.

We identify three views on the impact of intra-financial lending on the real economy. The first is the *financial efficiency* view associated with efficient markets views of the financial system (See, eg., Duffie [14]; Duffie [15]. See Crotty [9] for a critique of this view). This perspective holds that increases in intra-financial lending, reflecting securitization, the use of credit default swaps, and other new securities and risk management tools, are financial innovations that contribute to increases in useful liquidity and the efficiency of the financial intermediation process more generally. From this perspective, one would expect increases in intra-financial lending to be associated with sustainable increases in credit intermediation and real investment.[2]

The second perspective is the *financial instability* view. According to this view, increased intra-financial

resilience to shocks (See Acemoglu et al.[1] and Gai and Haldane [17]).

[2]See Crotty and Epstein [10], for a critique of the liquidity aspects of this argument.

lending reflects higher leverage and riskier counter-party structures, increased interconnectedness and as a result, increased vulnerability to financial runs and crises (DArista [11]; Gorton and Metric [18]; DArista and Epstein [12]; Shin [29]). Such increases in financial instability could lead to an upswing in credit flows in the bubble phase, but ultimately can lead to crises and therefore a decline in real investment and credit flows in the longer term.

The third perspective is the *financial inefficiency* or *rent extraction* perspective (Epstein and Crotty [16]; Turner [32]; Tobin [31]; Phillipon [27]; Bezmer [5]). This view holds that increased intra-financial lending and the financial innovation associated with it primarily reflects the attempt by financial institutions to extract more rent along the intermediation chain; as such it diverts capital from financing real investment. Intra-financial lending might or might not increase credit flows, but to the extent that it does these flows are designed to enhance rent extraction (speculative investments) rather than to contribute to real capital formation. Thus, according to this story, increased intra-financial flows are likely to be associated with reduced real investment and may work through a credit channel. (See, for example, Crotty [9], [8]) for a discussion of rent seeking and recent financial innovations). Here, intra-financial lending reflects an increase in "rent-extraction" from increased layers of financial intermediaries, raising the costs of capital and leading to more speculative and possibly dangerous financial investments, such as those associated with financial bubbles. In this case, capital is diverted from real investment. (Epstein and Crotty [16]). Credit flows to the real sector are expected to decline except for more speculative flows associated with the position taking by rent extracting financial actors.

This perspective suggests that intra-financial lending might be associated with what we call a "capital diversion" regime. "Capital diversion" can operate in one of several ways. The increased returns associated with complex chains of intra-financial lending raises the required rate of return associated with lending for real investments; alternatively, in a credit constrained economy, increased demand for credit for intra-financial lending will reduce credit available for investment outside of the financial sector. In either case, increased intra-financial lending would reduce credit flows and investment outside of the financial sector, all else equal, hence the term "capital-diversion."

In the empirical work that follows, we attempt to assess the relative validity of these three perspectives. More specifically, we employ a vector autoregression model using quarterly data for the United States for the period 1950Q1 to 2012Q4 to assess the relationship between intra-financial lending, credit supply and real investment. Our benchmark results suggest that a one percent shock to the intra-financial asset share is associated with a fall in investment of 2 percent after three quarters. We also provide evidence that this relationship may operate through a credit channel.

In addition, we examine the time-properties of these relationships and the possibility of structural breaks through rolling vector autoregressions and rolling impulse response functions. The results suggest that, since 1960, there have been two alternative regimes: one is a "capital diversion" regime, in which increases in intra-financial lending above the base-line amount appear to lead to deceases in credit supply and real investment; the second regime is a "financial bubble" regime, in which increases in intra-financial lending contribute to an unsustainable increase in credit and investment, as in a financial bubble. These two regimes appear to have been in force at different times over the period. The capital diversion regime dominated during most of the period. Between 1960 and 2000, increases in the share of intra-financial lending above the baseline were associated with declines in credit supply and real investment. But since the intra-financial lending share did not increase much until after 1980 there was very little negative impact of intra financial lending. Toward the latter part of the period, however, large increases in intra-financial lending did appear to have a negative impact on credit supply and investment. The second regime emerges during the boom years leading up to the 2008 financial crisis. In this case, the association between intra-financial lending and increased credit flows is probably associated with the unsustainable flows that contributed first to the bubble and then the crash of 2007-2008.

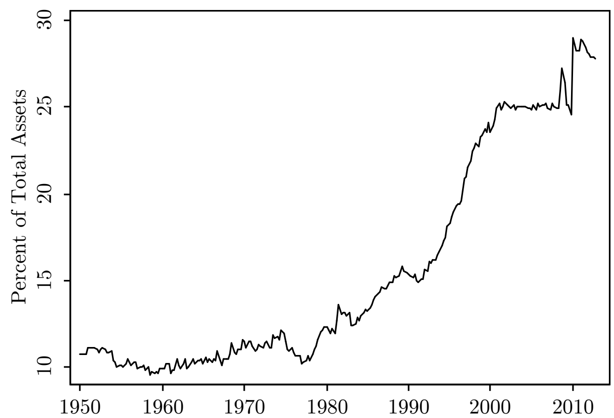
The rest of the paper proceeds as follows. Section 2 describes the key variables used in the VARs below and how the data was constructed. Section 3 presents the empirical results on the relationship between intra-financial flows, credit to the private sector, and private fixed investment from the baseline VAR model. Section 4 describes a series of robustness tests conducted in order to attempt to falsify the results. Section 5 then describes and presents the results from a simple VAR block bootstrapping routine to deal with the issue of residual non-normality in our baseline estimates. Section 6 examines the time properties of the parameter estimates and presents evidence that a structural break may have taken place after the year 2000. The final section concludes.

2 Data

We use aggregate quarterly data for the United States covering the period 1950-Q1 to 2012-Q4. The baseline model considers just three variables: real investment, intra-financial assets, and credit to the non-financial private sector. As discussed in Montecino, Epstein and Levina [25], measuring intra-financial assets is itself difficult since data on intra-financial claims is not collected by regulatory agencies nor disclosed by private financial institutions. Ideally, we would be able to observe the balance sheets of particular financial institutions and identify which assets represent liabilities for other banks. These in turn could be aggregated to yield the total amount of intra-financial assets. Our measure of intra-financial assets uses data from the Federal Reserve's Flow of Funds Accounts (henceforth, FOF) disaggregated by sectors and financial instruments. Because micro-level data is unavailable, we follow Bhatia and Bayoumi [6] in using the sectoral and instrument disaggregation of FOF credit data to match financial sector assets to their corresponding liabilities. Further details are provided in the Appendix as well as in Montecino et al. [25]

It is worth emphasizing that our variable of interest is not the level of intra-financial assets per se but the relative importance of these types of transactions in financial institutions' behavior. Thus, we divide our estimates of total intra-financial assets by the total assets of the financial sector to obtain the intra-financial asset share (IFA share). This variable has a straightforward interpretation: it captures the proportion of total financial institution credit that represents claims on other financial institutions (as opposed to, say,

Figure 1: Intra-Financial Asset Share



Source: Authors' calculations.

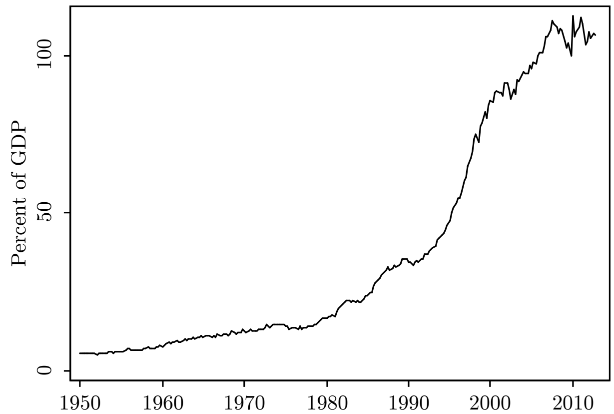
financing real investment opportunities).

The IFA share is shown for the period 1950-Q1 to 2012-Q4 in Figure 1. As can be seen in the figure, the IFA share grew dramatically beginning around 1980, increasing from around a tenth of all financial sector assets to over a quarter by the year 2001. The IFA share subsequently plateaued at around 25 percent until the onset of the 2008 financial crisis. The two spikes at the end of the series are driven almost entirely by the massive expansion of the Federal Reserve's balance sheet during the first and second rounds of quantitative easing. The leveling off of the IFA share, however, does not imply that intra-financial assets stopped growing during the 2000s. On the contrary, the 2000s were a period of rapid growth for intra-financial assets, but this was outpaced by overall credit growth during the lead up to the financial crisis. In fact, expressing intra-financial assets as a share of GDP reveals a completely different trend, as can be seen in Figure 2.

Data on aggregate investment was obtained from the Bureau of Economic Analysis (BEA). In particular, we use national accounts data on real gross fixed capital formation at a quarterly frequency. In order to examine the interaction between investment, intra-financial assets, and credit, we also use data on aggregate credit for the same period. We use a broad measure of credit: total credit to the non-financial sector deflated by the GDP deflator. In other words, we consider all financial sector assets that represent claims on the rest of the economy. This data was also obtained from the FOF.

Later robustness checks extend the baseline model by adding exogenous control variables. These include: a quarterly dummy variable indicating whether or not the United States was in a recession at the time; an index of real corporate profits; and the yield on the 3-month Treasury Bill to proxy for the effects of monetary policy. Data on corporate profits come from the BEA and are introduced to capture an alternative source of funding for financing investment. If some firms are credit constrained and finance investment through retained earnings then one would expect corporate profits to influence investment rates. The recession dummy variable was constructed using the recession dating by the National Bureau of Economic Research

Figure 2: Intra-Financial Assets as a share of GDP



Source: Authors' calculations.

(NBER) and is meant to control for cyclical variations in all three endogenous variables. The yield on the 3-month T-Bill was obtained from the Federal Reserve.

All three of our main variables of interest have been de-trended.[3] This is done to render the data stationary since standard Dickey-Fuller and Phillips-Perron tests for the presence of unit roots fail to reject the null that the data is stationary. These test results are shown in Table 1. The de-trended IFA share, credit, and investment are shown in Figure A.2.

3 Baseline VAR Results

The baseline model in (1) is a second-order vector autoregression with three endogenous variables: real gross capital formation, the IFA share, and real credit to the non-financial corporate sector.

$$\mathbf{y}_t = \mathbf{C} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \mathbf{u}_t \quad (1)$$

where $\mathbf{C}$ is a vector of constants, $\mathbf{u}_t$ is a vector of disturbance terms, and $\mathbf{y}_t$ is the vector of endogenous variables with:

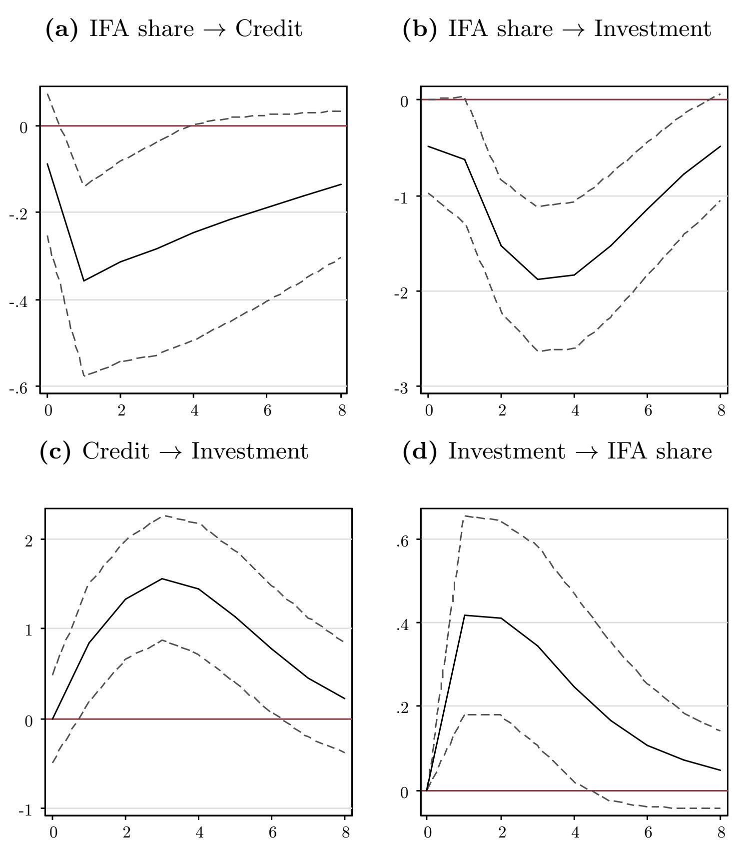
$$\mathbf{y}_t = \begin{bmatrix} \text{IFA share} \\ \text{Credit} \\ \text{Investment} \end{bmatrix} \quad (2)$$

It is worth noting that standard lag-selection order criteria recommend three alternative lag orders for the VAR: one, two, or seven lags. Our baseline specification, as well as the bootstrapped and rolling VAR models employed below, include two lags. However, we consider the two alternative specifications as additional robustness checks in the next section.

[3]The variables were de-trended using a Hodrik-Prescott filter. The smoothing parameter was set to 1600, as is standard for quarterly data.

The baseline estimates are reported in Table 3 and the impulse response functions are shown in Figure 3. The IFA share appears to have a strong, negative lagged effect on investment and the coefficient on the second lag is significant at the one percent level. The baseline estimates suggest that a one percent shock to the IFA share leads to around a two percent slowdown in investment after three quarters. As expected, credit supply has a strong and significant positive effect on aggregate investment. The coefficients on the first lag is significant at the one percent level. As can be seen in the impulse response function, a one percent shock to credit supply increases investment by around one and half percentage points after three quarters. Finally, the IFA share appears to have a statistically significant but weak negative effect on credit supply in the short-run.

Figure 3: Baseline impulse response functions. Panel (a) shows the effect of a one percent shock to the IFA share on investment after t quarters; (b) shows the effect of a one percent credit shock on investment; (c) shows the effect of a shock to investment on the IFA share; and (d) shows the effect of a shock to the IFA share on credit.



Source: Authors' calculations.

These baseline results are consistent with the hypothesis that the IFA share affects aggregate investment through the provision of credit to the private sector. A shock to the IFA share has a negative short-run effect on credit supply. Since firms appear to be credit constrained, as evidenced by the strong immediate positive effect of credit on investment, this should depress investment in subsequent periods. We refer to this as the "capital diversion" regime.

Granger causality test results are reported in Table 4. As can be seen in the table, we fail to reject the null hypothesis that the endogenous variables do not granger cause the dependent variable in each of the three specified equations. However, the baseline model appears to exhibit residual non-normality. As can be seen in Table 5, the Jarque-Bera test that the residuals are normally distributed is rejected at the one percent level for both the investment and IFA share equations. This issue is potentially quite severe as it calls into question inference based on the standard t-tests. We deal with the problem of residual non-normality below by implementing a block bootstrapping routine. The baseline model also exhibits residual autocorrelation. The Lagrange multiplier test rejects the null hypothesis that the residuals are not serially correlated at the one percent level. This also violates the models assumptions. However, this is only the case with one and two lags: once seven lags are included the model no longer exhibits autocorrelation.

4 Robustness Tests

In this section we submit the baseline model to a series of robustness tests. These can be summarized in three parts: (1) the inclusion of additional exogenous control variables; (2) restricting the sample period to 1950Q1-1999Q4; and (3) considering specifications with one, two, and seven lags, as recommended by lag-selection order criteria. The extended model is given by:

$$\mathbf{y}_t = \mathbf{C} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{B}_1\mathbf{x}_t + \cdots + \mathbf{B}_p\mathbf{x}_{t-p} + \mathbf{u}_t \tag{3}$$

where as before $\mathbf{C}$ is a vector of constants, $\mathbf{A}_p$ is the matrix of coefficients on the endogenous variables for the p-th lag. $\mathbf{y}_t$ and $\mathbf{x}_t$ are, respectively, the vectors of endogenous and exogenous variables, with:

$$\mathbf{y}_t = \begin{bmatrix} \text{IFA share} \\ \text{Credit} \\ \text{Investment} \end{bmatrix} \qquad \text{and} \qquad \mathbf{x}_t = \begin{bmatrix} \text{Recession Dummy} \\ \Delta\text{Log Profits} \\ \text{T-bill} \\ \text{Decade Dummy} \end{bmatrix} \tag{4}$$

As discussed above, the exogenous variables include a dummy for NBER-dated recession quarters, the log change of an index of real corporate profits, the yield on the three month Treasury Bill, and a decade dummy. The recession dummy is intended to control for cyclical variations in the endogenous variables while the corporate profits index proxies for the availability of funds to finance investment other than through borrowing (i.e. retained earnings). The 3-month Treasury Bill is intended to capture the effects of monetary policy and the decade dummy captures long-term differences across decades.

The results from the robustness tests are reported for all three lag orders in Tables 6 through 8. For the sake of exposition, we restrict our attention to the investment equation.[4] Each table reports six alternative specifications with alternating exogenous variables, each denoted by a check mark at the bottom of the table, as well as two distinct sample periods. The NBER recession dummy and 3-month Treasury are included in all six specifications while corporate profits are included in specifications (3) and (6). The specifications with the restricted sample appear in columns (4) through (6).

In order to interpret the results, what matters is not so much the coefficient estimates on their own but their dynamic interactions. Thus, we also calculate the orthogonalized impulse response functions of the investment equation for a one percent shock to the IFA share. These are reported for each of the six alternative specifications and for all three lag orders (Tables 9 through 11).

The key take away from these robustness exercises is that the negative effect of the IFA share on investment appears highly robust. In the case with one lag (Table 6), all variables are significant at the one percent level across all six specifications. Interestingly, the coefficients on the IFA share and credit are somewhat larger in the restricted sample, supporting the hypothesis of a structural break. However, all six specifications exhibit autocorrelation when only one lag is included. The results are similarly consistent across the alternative specifications when two lags are considered (Table 7). In this case, the negative coefficient on the IFA share also increases in absolute value in the restricted sample (specifications (4) through (6)). The estimated response of investment to an IFA share shock is also consistently negative and significant in both cases (Tables 9 and 10).

Finally, the key results remain intact when seven lags are introduced across all six alternative specifications. Although the coefficients on the lagged IFA share are now only significant at the 10 percent level in specifications (1) through (3), the response of investment in the impulse response functions is still significantly negative at the 5 percent level (Table 11)[5]. When the sample window is restricted to 1950Q1-1999Q4 (specifications (4) through (6)), IFA share remains significantly negative in both the second and fourth lags at the 5 percent level and at the one percent level for the fourth lag in specification (6).

Nevertheless, it is important to keep in mind that the residuals are not normally distributed and as such the p-values on the coefficients are not reliable. We address this issue in the next section.

5 The Block Bootstrap

As noted above, the residuals in the baseline model are likely non-normal, which poses a problem for inference. To address this problem we implement a block bootstrapping routine and use it to construct a 95 percent confidence interval for our baseline estimates.[6] The main advantage of this approach is that we do not

[4] Full results are available from the authors on request.

[5] The seventh lag of the IFA share also has positive and significant coefficients in specifications (1) through (3) but this does not translate into a significantly positive dynamic response of investment in the orthogonalized impulse response functions, as shown in Table 8.

[6] The block bootstrap was first introduced by Künsch [24]. A recent survey of alternative time series bootstrapping methods is Härdle et al. [23].

impose any assumptions on the underlying distributions of the disturbance terms.

Because the data is time dependent, the standard bootstrapping approach of randomly drawing observations with replacement is not valid. This is because drawing observations completely at random would eliminate the relationship between observations across time. Instead, we implement a "block sampling" routine that randomly draws with replacement sub-periods of length k from the full 1950-2012 sample. In other words, given a specified block length, the routine randomly samples k contiguous observations from the full sample.

Let T be the total number of periods and M be the number of endogenous variables. The T by M matrix of observations can be written as:

$$\underset{TXM}{\mathbf{Y}} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1M} \\ y_{21} & y_{22} & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ y_{T1} & y_{T2} & \cdots & y_{TM} \end{bmatrix} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_T \end{bmatrix} \tag{5}$$

where $\mathbf{y}_t$ is a one by M vector containing the t-th observation for all variables M. Therefore, given a block length k, the block sampling routine randomly draws with replacement a subsample of contiguous observations indexed by j:

$$\underset{kXM}{\mathbf{Y}_j} = \begin{bmatrix} \mathbf{y}_{s_j} \\ \mathbf{y}_{s_j+1} \\ \vdots \\ \mathbf{y}_{s_j+k-1} \end{bmatrix} \tag{6}$$

where s_j is the first period of block j. The first period s_j is a random variable uniformly distributed across 0 and $T-k$.

$$s_j \sim unif(0, T-k) \tag{7}$$

It's important for $s_j \leq T-k$ because otherwise we would end up with blocks of different period lengths. For example, suppose the randomly drawn block starts in 2000 but the data only goes up to 2012. If the block size is set greater than 12 years, then this block would be constrained in size.

The next step is to fit the VAR model using the observations in block j and obtain the parameter estimates $\hat{\mathbf{A}}_j$. This process is then repeated R times. That is, the routine will draw R subsamples from the data and obtain parameter estimates for each draw.[7] Once the R parameter estimates are obtained, these can used to construct a distribution of the model parameters as well as confidence intervals for hypothesis testing.

The 95 percent confidence interval was constructed by simply sorting the coefficients estimated from the randomly drawn blocks and calculating the upper and lower bound ranks. Let p be the percentile and n stand for the observation's rank. The ranks are calculated as:

$$n_p = int\left(\frac{p}{100} \cdot R + \frac{1}{2}\right) \tag{8}$$

[7] Note that for a given block length k and a total number of observations T, the maximum possible number of distinct blocks is $T-k+1$.

where $int(\cdot)$ converts numbers into their nearest integer and R is the number of replications (and hence also the number of estimated coefficients). The final step, is to extract the relevantly ranked parameter estimates and use them as the 95 percent confidence interval.

We consider a case with 500 repetitions and a block size of 30 years, that is $R = 500$ and $k = 120$ at a quarterly frequency.[8] Figure 4 shows the distribution of the estimated parameters and Table 12 reports the coefficients and bootstrap 95 percent confidence intervals. As can be seen below, the second and third lags of the IFA share in the investment equation are statistically and economically significant with the expected negative sign. The distribution of the 500 coefficient estimates for both these lags is well below zero. The results also show that the effect of credit to the private sector on investment is strongly positive and significant for the first three lags. The effect of the first lag of the IFA share on credit supply is statistically significant. As can be seen in the figure, its entire distribution lies below zero. However, as with the baseline results reported above, its magnitude remains modest and the confidence interval's upper bound is only barely negative (-0.04).

Therefore, these estimates suggest that the residual non-normality identified above does not meaningfully alter our baseline results. The IFA share continues to have a statistically significant negative effect on investment. Moreover, this negative effect still appears to operate via the credit channel, though the effect is modest.

6 Evidence From Rolling VARs

In this section we examine the properties of the parameter estimates across time. Specifically, we are interested in the stability of the estimated relationship between the IFA share, investment, and credit, and whether or not major changes in the parameter estimates and impulse response functions have occurred at any points in the sample period. This is motivated in part by the major observed shifts in the IFA share. In particular, the dramatic leveling off or plateau beginning in the year 2000 (see Figure 1) could be driven by some type of structural break. Another motivation is the possibility that intra-financial lending affects credit and investment differently during boom times and busts, and thus multiple regimes exist.

Similar to the block bootstrap discussed above, a rolling VAR draws samples of sub-periods from the full set of observations and fits the model for each sub-period.[9] However, instead of drawing the sample observations at random, a rolling VAR estimates the model for a given "window" of observations and then repeats the process by advancing the window a certain amount of time (a "step). The routine obtains parameter estimates across time and allows one to assess how these change over a long period or if there

[8]This is larger than the "rule of thumb" optimal block length of $k = T^{1/3}$. Efficiency in block bootstraps faces a tradeoff between long blocks, which are superior at preserving the time-dependent structure of the data, and short blocks, which ensure the sample draws are random. Optimal block length is discussed in Hall, Horowitz, and Jing [22]. In this case, given our limited quarterly sample size, we opted for a longer block length. The results are robust to alternative numbers of repetitions.

[9]See Blanchard and Galí [7] and Gronwald [20] for recent applications of this technique. Earlier examples include Wong [33], Guirguis and Schmidt [21], and Park and Ratti [26].

are any discrete changes. The resulting parameter estimates can then be used to calculate separate impulse response functions for each sample period.

We use a rolling VAR with a window w of 80 observations (20 years) and a step size of one quarter. This implies 175 windows in total, which will be denoted by W. That is, the routine estimates the model in equation (9) using 20 year windows advanced one quarter at a time.

$$\mathbf{y}_t^w = \mathbf{C} + \mathbf{A}_1^w \mathbf{y}_{t-1}^w + \mathbf{A}_2^w \mathbf{y}_{t-2}^w + \mathbf{u}_t^w \qquad \forall\, w \in W \tag{9}$$

To calculate the impulse response functions for each window w we impose a recursive, triangular structure on the baseline model. That is, the reduced form disturbance, $\mathbf{u}_t^w$, is decomposed as:

$$\mathbf{u}_t^w = \mathbf{B}^w \mathbf{e}_t^w \tag{10}$$

where $\mathbf{e}_t^w$ is a vector of structural shocks and $\mathbf{B}^w$ is a matrix of contemporaneous correlation parameters for each window w such that:

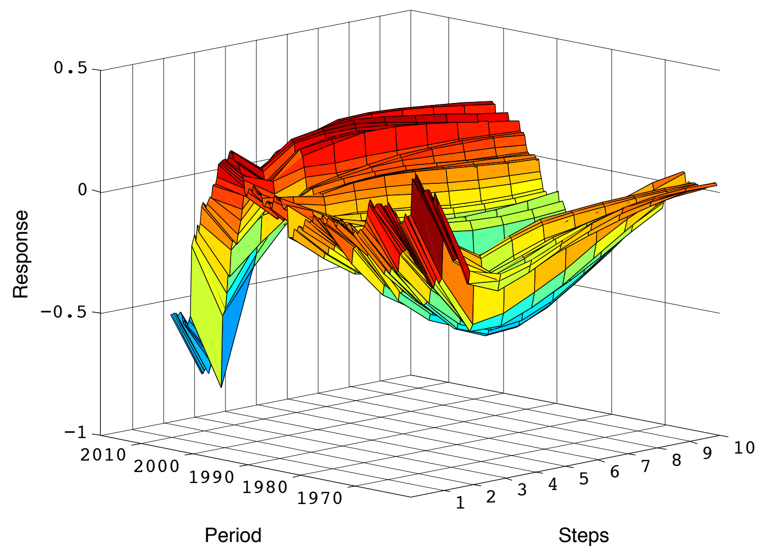
$$\mathbf{B}^w = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \tag{11}$$

This structure implies that the IFA share does not contemporaneously affect credit or investment but credit is contemporaneously affected by the IFA share. Investment in turn is contemporaneously affected by both credit and the IFA share. The model in equations (9) through (11) yields 175 estimates for each parameter sorted by the time period of the sample window. These translate into three-dimensional impulse response functions. We consider the impact of a one percent shock to the IFA share and calculate the dynamic responses of credit and investment ten quarters after the shock. These are shown in Figure 5, where the x-axis measures the steps or number of quarters after the shock (see Figure A.3 for cross-sections of the rolling impulse reposes). The y-axis measures the end-period of the sample window while the vertical z-axis measures the response. These are simply ordinary impulse response functions with the added dimension of the sample window. If a cross-sectional "slice is taken at any given sample window, the figures reduce to a typical two-dimensional impulse response.

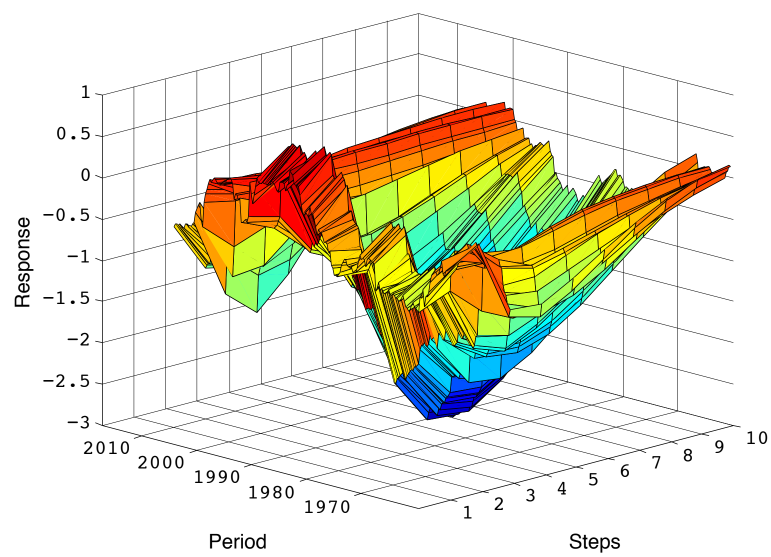
The rolling VAR impulse response functions are consistent with the presence of two regimes: a "capital diversion" regime where intra-financial lending is associated with lower credit and lower investment, and a financial bubble regime where intra-financial lending complements credit and leads to higher aggregate investment but in a way that might not be sustainable. More specifically, this second regime appears to broadly coincide with rapid financial expansion and high growth, particularly during the decade leading up to the 2008 financial crisis. The first regime, on the other hand, appears to hold during the rest of the sample.

Figure 5: Rolling VAR impulse response functions. Panel (a) reports the response of credit to a one percent shock to the IFA share while panel (b) reports the response of investment. The x-axis corresponds to the number of steps or quarters after the initial shock while the y-axis measures the end-period of the sample window. The vertical z-axis measures the response of each variable in percentage terms.

(a) IFA share ⟶ Credit



(b) IFA share ⟶ Investment



Source: Authors' calculations.

Panel (a) of Figure 5 shows the dynamic response of credit to a one percent IFA share shock. Credit appears to respond negatively to an IFA share shock throughout the majority of the sample - although there is significant variation in the magnitude of the response. The negative response is moderate during the earlier sample windows. For instance, during the first window (1950-Q1 to 1969-Q1) credit falls around 0.16 percent after three quarters. However, as time progresses, the negative response becomes significantly stronger. As the estimation window reaches the 1960s the fall in credit exceeds 0.5 percent after three quarters.

The dynamic response of investment to a one percent IFA share shock follows a similar time pattern. As can be seen in panel (b), the rolling impulse response function is "bowl-shaped, which implies that the negative effect on investment becomes much more pronounced as the sample window advances towards the middle of the sample. At the beginning of the sample, for estimation windows between the early 1950s to early 1970s, a one percent IFA share shock is associated with a fall in credit of between 0.5 and 1 percent after four quarters. This contrasts with responses during estimation windows closer to the middle of the sample. For instance, during the estimations window from 1970-Q1 to 1989-Q4, a one percent IFA share shock is associated with as large as a 2.5 percent fall in investment after five quarters.

This relationship begins to reverse during the 1990s. The negative response of credit to an IFA share shock progressively weakens before eventually becoming positive during the early 2000s. This new positive relationship persists until the estimation window reaches the late 2000s, roughly coinciding with the onset of the financial crisis. At its peak, credit exhibits a 0.25 percent positive response to a one percent IFA share shock for estimation windows ending around the year 2005. Similarly, once the estimation window reaches the 2000s the response of investment flattens out and becomes slightly positive. For estimation windows ending around the mid 2000s, the IFA share shock is associated with around a 0.2 percent increase in investment.

However, the responses of both credit and investment once again reverse sharply during the end of the sample. This dramatic reversal in the responses of both variables coincides with the onset of the 2008 financial crisis. For instance, after remaining positive throughout windows ending in the 2000s, by the last estimation window (1993-Q1 to 2012-Q4), credit falls by 0.76 percent after two quarters. During this same window, a one percent IFA share shock is associated with around a 1.2 percent decline in investment.

This brief period leading up to the financial crisis is consistent with the financial instability view and contrasts sharply with the patterns observed throughout the rest of the sample. The abrupt changes in the estimated responses of credit and investment suggest that some form of structural break or change in regime took place during the late 1990s, a period of rapid financial innovation and a vast expansion in the size and scope of the financial sector. Accordingly, we refer to this as the "financial instability regime", where increases in intra-financial lending may lead to credit growth but this growth is likely unsustainable.

Throughout the rest of the sample the estimated responses of credit and investment are more in line with the baseline estimates presented in previous sections: the data exhibit a "capital diversion" regime where increases in intra-financial lending negatively impact investment and credit. It is worth noting that this does not necessarily imply that intra-financial lending has had large negative effects on investment throughout the majority of the sample. This is mainly because the IFA share did not grow very significantly until the late 1980s (see Figure 1). In other words, these results suggest that intra-financial lending must have had an overall small negative effect on investment during the so-called golden age between the 1950s and 1960s since the IFA share was stable throughout this period. This in turn implies that the sustained increases in the IFA share during the late 1980s and 1990s must have had large cumulative negative impacts on investment.

These results seem consistent with the view that excessive intra-financial lending is associated with declines in credit availability for real investment, except during periods associated with asset bubbles. During asset bubble periods, intra-financial lending and credit appear to support each other, resulting in temporary but unstainable increases in real investment. These results provide no support for the *financial efficiency* perspective on intra-financial lending; and they provide evidence for both the *financial inefficiency/rent-extraction* perspective and the *financial instability* perspectives as operating at different times.

7 Conclusion

This paper has empirically examined the relationship between intra-financial lending, credit supply, and aggregate fixed investment in the US in the post War-period. It finds, overall, that increases in intra-financial assets as a share of total financial assets are associated with slower investment. This negative relationship survives a wide range of robustness tests and the implementation of a block bootstrapping routine to construct reliable confidence intervals. Our results also provide partial evidence that this negative relationship operates to some extent through the credit channel: intra-financial lending appears to be associated with credit supply temporally prior to the fall in investment.

While these results predominate during the period, we also found evidence of structural change during the period, manifested in the existence of two regimes: "a capital diversion" regime, described above, and, for a shorter period during the 2000s, a "financial bubble" regime, in which intra-financial lending, credit and investment had a positive feedback loop in an unsustainable boom, culminating in the financial crisis of 2008.

These results seem to be inconsistent with a "financial efficiency" view of intra-financial lending associated with mainstream financial theory and the efficient markets hypothesis. That is to say, increased intra-financial lending does not lead to greater risk sharing, more useful liquidity and higher investment; rather it appears to lead to lower real investment, suggesting a capital diversion and rent extraction role for intra-financial lending. Our results also suggest that the only time that more intra-financial lending appears to be even moderately associated with more investment is during financial asset bubbles, when, temporarily, intra-financial lending is associated with both more credit and investment, neither of which is sustainable as the financial bubble bursts. Our results also suggest that these connections between intra-financial lending and real investment appear to operate at least partly through a credit channel.

These results should be seen as a preliminary exploration of aggregate relations. Without further study, we should be weary to make any definitive causal inferences. We are acutely aware that the credit channel may not be the only or even the most important mechanism for explaining the apparent negative relation between intra-financial lending and investment. An alternative explanation could be that our measure of intra-financial lending merely proxies for broader trends in the financial and real sectors. In this case, the perceived negative relationship could be picking up the effects of other factors, such as increases in firm level volatility (as identified by Davis [13]). Thus, while our results provide no support for the efficient markets view of intra-financial lending, further work is still necessary to improve our understanding of the precise causal mechanisms between intra-financial flows, credit and real investment.

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A Calculating the Intra-Financial Asset Share

This appendix briefly describes how we constructed the IFA share variable. As discussed above, the Flow of Funds does not provide data on the network structure of financial assets and liabilities. Instead, it contains data organized in two broad ways: (1) instrument types (i.e. corporate bonds, deposits, loans, etc.) and (2) sectoral classifications (i.e. commercial banks, households, funding corporations, etc.). Following Bhatia and Bayoumi (2012)[6], we approximate the amount of intra-financial assets by combining the two types of series.

To illustrate the calculations, consider the following simplified balance sheet:

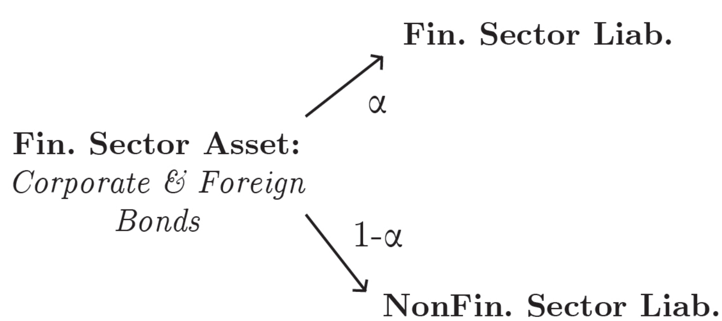
$$a_1 + a_2 = l_1 + l_2 \tag{A.1}$$

where $1, 2$ are different financial instruments and j indexes the different sectors of the economy. This is what we observe in the Flow of Funds. However, what we would ideally observe is sector j's total assets that represent claims on specific sectors. Of course, in this case we are specifically interested in assets held by financial institutions that represent claims on other financial institutions. That is, we would ideally observe:

$$a_f^f + a_f^n = l_f^f + l_f^n \tag{A.2}$$

where the subscripts f and n respectively denote the financial and non-financial sectors and a_n^f, for instance, is the financial sector's claims on the non-financial sector. Nevertheless, although we cannot directly observe a_f^f, we can make assumptions about the proportions of financial sector assets that become financial sector liabilities. By definition, a certain share α_i of financial sector assets in each instrument category must correspond to financial sector liabilities. This is illustrated in **Figure A.1**.

Figure A.1



Therefore, in order to approximate the amount of intra-financial assets in each instrument category we assume:

$$\alpha_i = \frac{l_i^f}{l_i} \tag{A.3}$$

That is, we assume the share of intra-financial assets in each instrument is proportional to the financial sector's share of the total liabilities in each particular instrument. Once we have calculated α_i for each instrument i, we can calculate the amount of intra-financial assets by simply multiplying it by the financial sector's total assets of instrument i. That is:

$$a_{if}^{f} = \alpha_i a_i^f \tag{A.4}$$

If N is the total number of instruments, then total intra-financial assets in the economy is thus given by:

$$a_f^f = \sum_{i=1}^{N} \alpha_i a_i^f \tag{A.5}$$

The IFA share is thus calculated as:

$$\text{IFA share} = \frac{a_f^f}{a} \quad \text{where} \quad a = \sum_{i=1}^{N} a_i \tag{A.6}$$

Table 1: Dickey-Fuller and Phillips-Perron unit root tests. In both cases the null hypothesis is that the data has a unit root.

	Dickey-Fuller	Phillips-Perron	
	$Z(t)$	$Z(rho)$	$Z(t)$
IFA share	0.915	0.878	0.965
Credit	-0.235	0.046	0.142
Investment	-0.876	-1.434	-1.119

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 2: Summary statistics. The IFA share, credit, and investment variables are de-trended. The recession dummy was constructed using the official NBER recession dates. T-bill is the yield on the 3-month Treasury while corporate profits refers to the log difference of real corporate profits.

	Mean	Std. Dev.	Min.	Max.	N
IFA share	0	2.665	-8.302	9.170	252
Credit	0	2.415	-6.096	7.232	252
Investment	0	7.687	-24.647	19.076	252
Recession dummy	0.146	0.354	0	1	253
3-month t-bill	4.521	3.02	0.01	15.49	254
Corporate profits	1.606	6.491	-33.358	30.362	251

Source: Authors' calculations.

Table 3: Baseline VAR estimates.

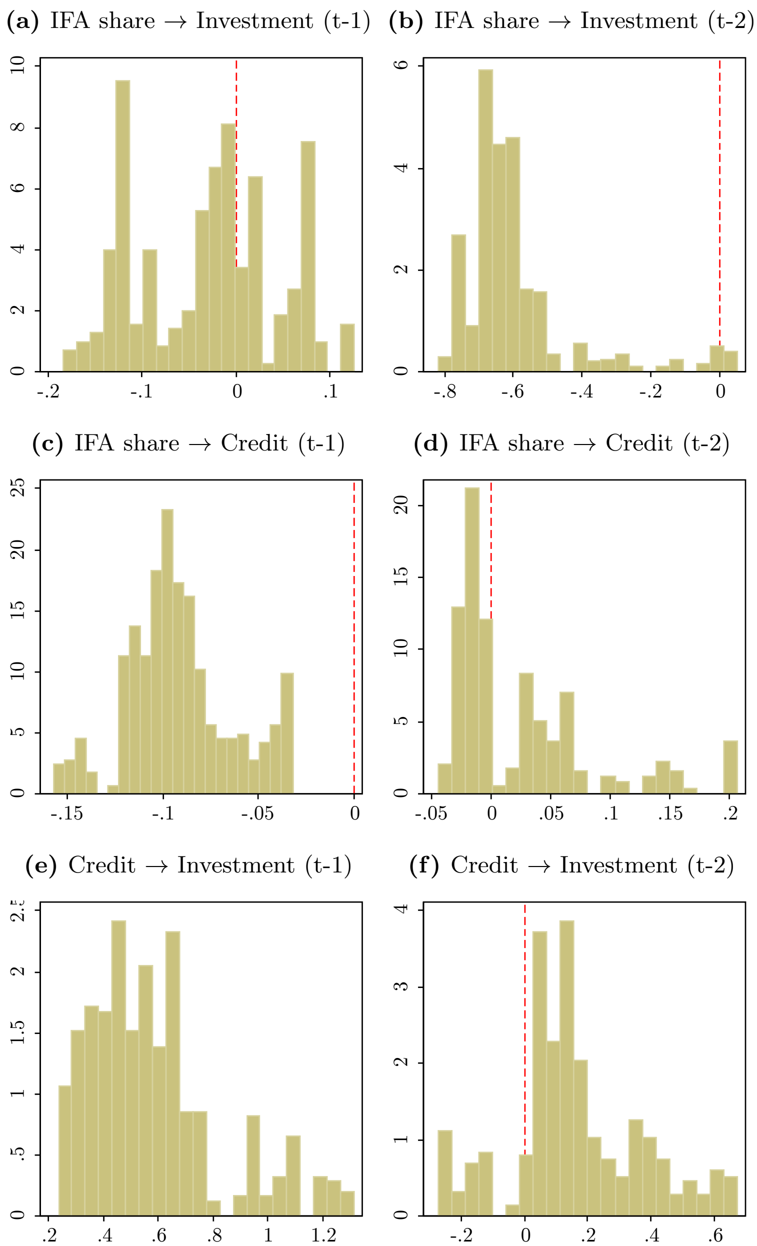
VARIABLES	(1) IFA share	(2) Credit	(3) Investment
IFA share (t-1)	0.580***	-0.134***	-0.068
	(0.063)	(0.041)	(0.124)
IFA share (t-2)	0.050	0.082**	-0.386***
	(0.061)	(0.040)	(0.121)
Credit (t-1)	-0.250***	0.897***	0.642***
	(0.095)	(0.063)	(0.188)
Credit (t-2)	0.268***	-0.134**	-0.162
	(0.096)	(0.063)	(0.191)
Investment (t-1)	0.107***	0.023	0.899***
	(0.031)	(0.020)	(0.061)
Investment (t-2)	-0.047	0.004	-0.202***
	(0.030)	(0.020)	(0.060)
Constant	-0.003	-0.010	0.054
	(0.126)	(0.083)	(0.249)
Observations	250	250	250

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

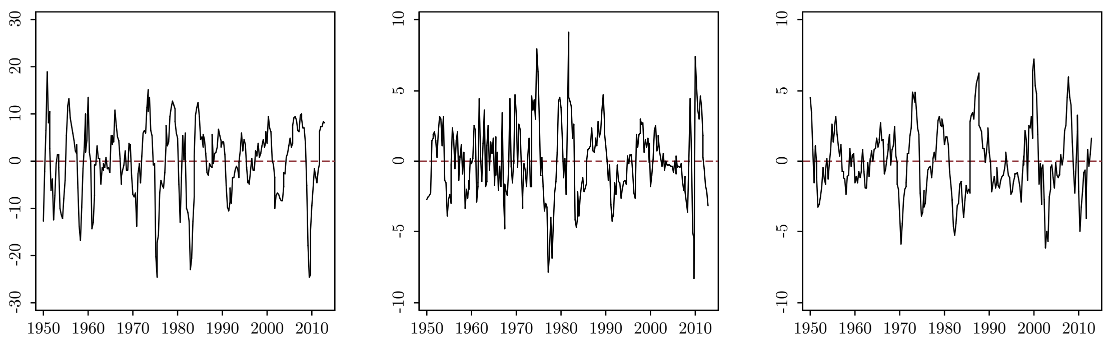
Figure 4: Distribution of block bootstrap point estimates. Panels (a) and (b) show the distributions of the coefficient on the first and second lags, respectively, of the IFA share in the investment equation. Panels (c) and (d) show similar results for the IFA share in the credit equation while (e) and (f) show the results for credit in the investment equation.



Source: Authors' calculations.

Figure A.2: De-trended baseline variables.

(a) Investment (b) IFA Share (c) Credit



Source: Authors' calculations.

Table 4: Granger causality tests for the baseline model.

Equation	Excluded	χ^2
Investment		
	IFA share	18.38***
	Credit	20.162***
	All	46.246***
IFA share		
	Investment	15.510***
	Credit	8.302**
	All	31.978***
Credit		
	Investment	4.318
	IFA share	10.525***
	All	13.466***

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 5: Jarque-Bera residual normality test. The null hypothesis is that the residuals are normally distributed.

	χ^2
IFA share	733.324***
Credit	23.418***
Investment	21.054***
All	777.797***

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 6: Alternative specifications for the investment equation including 1 lag. Columns (1) through (3) report the estimates for the full sample (1950Q1 to 2012Q4) while columns (4) through (7) report the estimates for the restricted sample (1950Q1 to 1999Q4). Checkmarks (✓) at the bottom of each column indicate that the additional control variable is included in the specification.

	1950Q1-2012Q4			1950Q1-1999Q4		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
IFA share (t-1)	-0.288***	-0.330***	-0.272***	-0.386***	-0.388***	-0.294***
	(0.094)	(0.095)	(0.097)	(0.112)	(0.112)	(0.114)
Credit (t-1)	0.498***	0.528***	0.549***	0.738***	0.749***	0.759***
	(0.109)	(0.109)	(0.111)	(0.141)	(0.144)	(0.144)
Investment (t-1)	0.642***	0.627***	0.648***	0.589***	0.568***	0.587***
	(0.038)	(0.038)	(0.039)	(0.045)	(0.046)	(0.046)
Constant	0.692	0.959	0.626	0.227	0.747	0.347
	(0.451)	(0.673)	(0.683)	(0.592)	(0.717)	(0.719)
Observations	250	250	249	198	198	197
LM test (p-value)						
Lag 1	0.002	0.001	0.001	0.002	0.004	0.006
Lag 2	0.866	0.874	0.795	0.653	0.755	0.607
Additional controls						
Recession dummy	✓	✓	✓	✓	✓	✓
T-bill	✓	✓	✓	✓	✓	✓
Decade dummies		✓	✓		✓	✓
Corporate profits			✓			✓

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 7: Alternative specifications for the investment equation including 2 lags. Columns (1) through (3) report the estimates for the full sample (1950Q1 to 2012Q4) while columns (4) through (7) report the estimates for the restricted sample (1950Q1 to 1999Q4). Checkmarks (✓) at the bottom of each column indicate that the additional control variable is included in the specification.

	1950Q1-2012Q4			1950Q1-1999Q4		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
IFA share (t-1)	-0.113	-0.151	-0.132	-0.060	-0.057	-0.055
	(0.113)	(0.114)	(0.114)	(0.139)	(0.140)	(0.138)
IFA share (t-2)	-0.228**	-0.240**	-0.231**	-0.459***	-0.454***	-0.386***
	(0.112)	(0.111)	(0.112)	(0.141)	(0.140)	(0.141)
Credit (t-1)	0.539***	0.539***	0.555***	0.579**	0.538**	0.557**
	(0.171)	(0.171)	(0.170)	(0.230)	(0.237)	(0.233)
Credit (t-2)	-0.128	-0.105	-0.107	0.120	0.140	0.111
	(0.174)	(0.173)	(0.173)	(0.243)	(0.243)	(0.242)
Investment (t-1)	0.708***	0.682***	0.643***	0.630***	0.622***	0.547***
	(0.064)	(0.064)	(0.067)	(0.070)	(0.071)	(0.076)
Investment (t-2)	-0.062	-0.035	0.028	-0.037	-0.030	0.074
	(0.058)	(0.059)	(0.066)	(0.063)	(0.063)	(0.074)
Constant	0.696	0.951	0.573	0.303	0.803	0.331
	(0.438)	(0.659)	(0.682)	(0.561)	(0.690)	(0.708)
Observations	250	250	249	198	198	197
LM test (p-value)						
Lag 1	0.408	0.268	0.051	0.031	0.087	0.019
Lag 2	0.058	0.104	0.261	0.006	0.014	0.033
Additional controls						
Recession dummy	✓	✓	✓	✓	✓	✓
T-bill	✓	✓	✓	✓	✓	✓
Decade dummies		✓	✓		✓	✓
Corporate profits			✓			✓

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 8: Alternative specifications for the investment equation including 7 lags. For the sake of conciseness, we only report the coefficients for the lagged IFA share. Columns (1) through (3) report the estimates for the full sample (1950Q1 to 2012Q4) while columns (4) through (7) report the estimates for the restricted sample (1950Q1 to 1999Q4). Checkmarks (✓) at the bottom of each column indicate that the additional control variable is included in the specification.

	1950Q1-2012Q4			1950Q1-1999Q4		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
IFA share (t-1)	0.047	0.029	0.105	0.148	0.136	0.176
	(0.118)	(0.118)	(0.123)	(0.146)	(0.147)	(0.143)
IFA share (t-2)	-0.195	-0.209	-0.173	-0.344**	-0.352**	-0.276*
	(0.129)	(0.128)	(0.134)	(0.163)	(0.163)	(0.158)
IFA share (t-3)	-0.062	-0.071	-0.160	-0.004	-0.018	-0.082
	(0.127)	(0.126)	(0.130)	(0.162)	(0.162)	(0.157)
IFA share (t-4)	-0.201*	-0.208*	-0.202*	-0.397**	-0.392**	-0.418***
	(0.121)	(0.121)	(0.120)	(0.155)	(0.154)	(0.149)
IFA share (t-5)	0.066	0.057	0.029	0.173	0.179	0.146
	(0.126)	(0.126)	(0.124)	(0.159)	(0.159)	(0.153)
IFA share (t-6)	0.042	0.029	0.039	-0.030	-0.027	0.005
	(0.126)	(0.126)	(0.124)	(0.161)	(0.160)	(0.155)
IFA share (t-7)	0.243**	0.257**	0.295***	0.178	0.183	0.188
	(0.112)	(0.112)	(0.112)	(0.141)	(0.141)	(0.137)
Constant	0.367	0.369	0.516	-0.313	-0.049	0.232
	(0.429)	(0.673)	(0.712)	(0.538)	(0.705)	(0.742)
Observations	245	245	244	193	193	192
LM test (p-value)						
Lag 1	0.426	0.020	0.026	0.565	0.477	0.306
Lag 2	0.706	0.819	0.055	0.284	0.345	0.020
Additional controls						
Recession dummy	✓	✓	✓	✓	✓	✓
T-bill	✓	✓	✓	✓	✓	✓
Decade dummies		✓	✓		✓	✓
Corporate profits			✓			✓

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 9: Response of investment to a one percent IFA share shock. Each column reports the orthogonalized impulse response functions for the alternative specifications of the investment equation including 1 lag in the VAR models. Columns (1) through (6) correspond to the specifications reported in Table 8. Asterisks ($*$) next to the response estimate indicate significance at the 5 percent level.

	1950Q1-2012Q4			1950Q1-1999Q4		
	(1)	(2)	(3)	(4)	(5)	(6)
Step	oirf	oirf	oirf	oirf	oirf	oirf
0	-0.491*	-0.593*	-0.570*	-0.489	-0.513	-0.458
1	-0.951*	-1.066*	-0.953*	-0.885*	-0.869*	-0.672*
2	-1.068*	-1.117*	-1.012*	-0.938*	-0.871*	-0.677*
3	-1.014*	-0.994*	-0.929*	-0.835*	-0.737*	-0.596*
4	-0.886*	-0.821*	-0.795*	-0.678*	-0.572*	-0.491*
5	-0.739*	-0.651*	-0.656*	-0.520*	-0.422*	-0.388
6	-0.598*	-0.505*	-0.529*	-0.384	-0.303	-0.300
7	-0.474*	-0.388*	-0.422*	-0.275	-0.214	-0.229
8	-0.370*	-0.298*	-0.334*	-0.194	-0.150	-0.174
9	-0.286*	-0.229*	-0.263*	-0.135	-0.106	-0.131
10	-0.220*	-0.176	-0.207*	-0.093	-0.076	-0.099
11	-0.168	-0.137	-0.163	-0.065	-0.055	-0.075
12	-0.128	-0.107	-0.129	-0.045	-0.041	-0.057

Source: Authors' calculations.

Table 10: Response of investment to a one percent IFA share shock. Each column reports the orthogonalized impulse response functions for the alternative specifications of the investment equation including 2 lags in the VAR models. Columns (1) through (6) correspond to the specifications reported in Table 8. Asterisks ($*$) next to the response estimate indicate significance at the 5 percent level.

	1950Q1-2012Q4			1950Q1-1999Q4		
	(1)	(2)	(3)	(4)	(5)	(6)
Step	oirf	oirf	oirf	oirf	oirf	oirf
0	-0.543*	-0.609*	-0.579*	-0.478	-0.477	-0.414
1	-0.650*	-0.739*	-0.663*	-0.307	-0.297	-0.228
2	-1.168*	-1.250*	-1.181*	-1.060*	-1.019*	-0.892*
3	-1.222*	-1.243*	-1.185*	-1.139*	-1.067*	-0.906*
4	-1.098*	-1.066*	-1.067*	-1.086*	-0.997*	-0.902*
5	-0.886*	-0.827*	-0.872*	-0.905*	-0.817*	-0.784*
6	-0.677*	-0.614*	-0.687*	-0.697*	-0.625*	-0.650*
7	-0.501*	-0.447*	-0.527*	-0.496	-0.447	-0.509*
8	-0.365	-0.326	-0.400*	-0.325	-0.302	-0.381
9	-0.264	-0.238	-0.302	-0.191	-0.191	-0.273
10	-0.190	-0.174	-0.227	-0.096	-0.112	-0.186
11	-0.136	-0.128	-0.169	-0.032	-0.060	-0.119
12	-0.097	-0.093	-0.126	0.006	-0.026	-0.071

Source: Authors' calculations.

Table 11: Response of investment to a one percent IFA share shock. Each column reports the orthogonalized impulse response functions for the alternative specifications of the investment equation including 7 lags in the VAR models. Columns (1) through (6) correspond to the specifications reported in Table 8. Asterisks (∗) next to the response estimate indicate significance at the 5 percent level.

	1950Q1-2012Q4			1950Q1-1999Q4		
	(1)	(2)	(3)	(4)	(5)	(6)
Step	oirf	oirf	oirf	oirf	oirf	oirf
0	-0.353	-0.385*	-0.303	-0.277	-0.292	-0.138
1	-0.266	-0.312	-0.091	0.093	0.056	0.222
2	-0.661*	-0.725*	-0.444	-0.398	-0.455	-0.226
3	-0.805*	-0.874*	-0.774*	-0.495	-0.578	-0.404
4	-0.936*	-1.003*	-0.960*	-0.937*	-1.020*	-0.940*
5	-0.510	-0.579*	-0.627*	-0.563	-0.631*	-0.551
6	-0.261	-0.335	-0.396	-0.498	-0.545	-0.456
7	0.194	0.165	0.112	-0.201	-0.213	-0.178
8	0.206	0.213	0.075	-0.182	-0.163	-0.261
9	0.294	0.323	0.178	-0.038	0.008	-0.098
10	0.391	0.429	0.352	0.018	0.083	-0.018
11	0.437	0.472	0.422	0.085	0.160	0.099
12	0.331	0.368	0.348	0.012	0.093	0.009

Source: Authors' calculations.

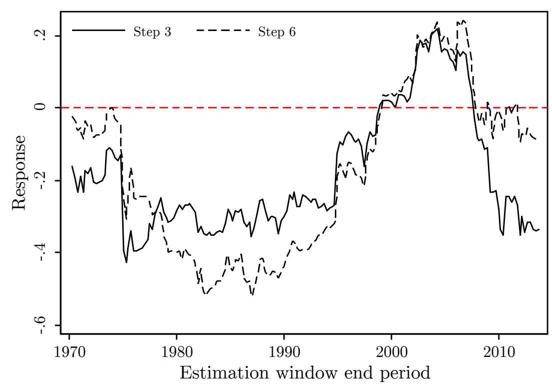
Table 12: Baseline VAR model with block bootstrapped confidence intervals. (1) Refers to the IFA share equation while (2) and (3) refer to the credit and investment equations, respectively. This VAR covers all 250 observations from the entire sample period (1950Q3-2012Q4). Asterisks (*) next to the point estimates denote significance at the 5 percent level.

	(1) IFA			(2) Credit			(3) Investment		
		95 C.I.			95 C.I.			95 C.I.	
VARIABLE	$\hat{\mathbf{A}}$	Lower	Upper	$\hat{\mathbf{A}}$	Lower	Upper	$\hat{\mathbf{A}}$	Lower	Upper
IFA (t-1)	0.580*	0.518	0.678	-0.134*	-0.148	-0.036	-0.068	-0.148	0.090
IFA (t-2)	0.050	0.000	0.118	0.082	-0.033	0.204	-0.386*	-0.767	-0.027
Credit (t-1)	-0.250*	-0.686	-0.086	0.897*	0.858	1.045	0.642*	0.250	1.205
Credit (t-2)	0.268*	0.186	0.649	-0.134*	-0.198	-0.047	-0.162	-0.247	0.607
Investment (t-1)	0.107*	0.067	0.177	0.023	-0.018	0.033	0.899*	0.600	1.186
Investment (t-2)	-0.047	-0.156	0.018	0.004	-0.020	0.051	-0.202*	-0.379	-0.065
Constant	0.000	-0.001	0.001	0.000	-0.001	0.001	0.001	-0.002	0.002

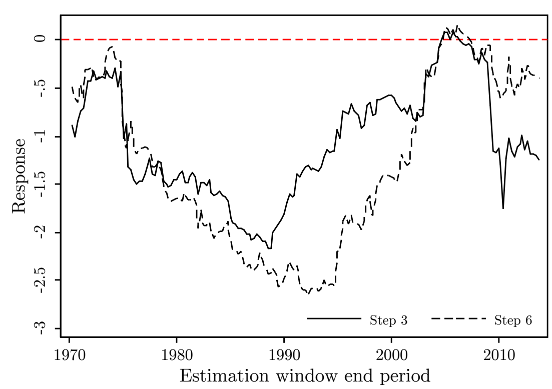
Source: Authors' calculations.

Figure A.3: Alternative view of rolling VAR impulse response functions. Panel (a) reports the response of credit to a one percent shock to the IFA share while panel (b) reports the response of investment. The solid and dash lines show the response after 3 and 6 steps, respectively. The x-axis corresponds to the end-period of the estimation window. The vertical axis measures the response of each variable in percentage terms.

(a) IFA share $\longrightarrow$ Credit



(b) IFA share $\longrightarrow$ Investment



Source: Authors' calculations.