Cointegration of US Income Inequality and Financial Sector Size

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1 Introduction

> "Which is more relevant: a rigorous demonstration as to how resources can be most efficiently allocated under ideal conditions that have never existed, or a much cruder exploration of how wealth and income came to be distributed as they in fact are and what might be done to affect the distribution of income in one way or another?"

Robert Gordon posed this question nearly four decades ago (Gordon (1976)). It has only become more urgent since as the recent global financial crisis and subsequent recession have increased economists research focus on inequality. Since the Kuznets (1955) conjecture of an inverted-U shaped relation between income inequality and economic growth, the literature has focused on two distinct areas: empirically measuring income inequality (e.g. top quantile's share of total income, Gini coefficient, Lorenz curves, Theils T) and its corresponding changes over time; and the theoretical determinants of income inequality. The latter models have then been tested against the former results to gauge their success in explaining inequality, thus employing a *specific-to-general* modeling approach.

Research by Piketty & Saez (2003) concerning the distribution of income in the United States, with continuously updated data through 2012, has demonstrated increasing skewness in the distribution of US income in the last forty years. The majority of the skewness, they've concluded, is driven by

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the top 0.01% of incomes. Kopczuk & Saez (2004) found that the top 0.01%'s changes in wealth in the last forty years also drove the broader changes in the shape of the distribution of wealth.

While the decline of the manufacturing sector over the last fifty years is a well-documented phenomenon in the developed world with widely debated effects, the consequences of the complimentary increase in the service sector, particularly the industries of financial services and insurance, is less well known. Philippon (2008) has recently begun examining the role of US financial sector size and its externalities.

Many economists (Krugman, Stiglitz (2012), S. Johnson, Epstein & Crotty (2012), Kumhof & Ranciere (2010)) have speculated as to the negative long term effects of both large increases in inequality as well as the financialization of the US economy–that is, the disproportionate growth of the financial services, insurance, and real estate sectors relative to the rest of the economy over the past thirty years.

Of course one possibility may be a wealth effect from income inequality. That is, wealthier individuals would demand more financial services and thus the mechanism may run from income inequality to an increase in finance. Philippon & Reshef (2013) find support for this hypothesis, however only in the US and only in the last thirty years. More importantly, over a longer time series (i.e. since 1950), inequality is decreasing while finance grows as a share of the total economy.

Thus the objective of this paper is to

1. understand how US income inequality and financial sector size may be related by examining the long-run relationship between them, and

2. consider how they respond to each other's short-run shocks or periods of disequilibrium.

Given the severity of the recent crisis and the global economy's persistent precarious state, understanding how these other variables interact with inequality, generating macroeconomic effects, is of critical importance. The greater aim is to understand when pushing forces in the economy, driving long-run trends, deviate too much and how they are pulled back towards equilibrium, not necessarily just this subset of variables.

1.1 Literature

Existing theory on within-country income inequality and financial development is conflicting. While this paper considers financial sector size, not the level of financial development, empirical research often relies on the amount of financial intermediation as a proxy for development, which also identifies size.

Most famously, Kuznets (1955) conjectured an inverted-U relationship between income inequality and growth more broadly. Greenwood & Jovanovic (1990) use this baseline nonlinear relationship to consider the effect of financial development at various points along this hypothetical curve, or rather the tradeoff between growth and inequality. Their model specifies a process in which initial economic development yields little growth and no financial development. As a financial "superstructure" forms, the savings rate and income inequality increase, but so does output. At maturity, an economy features a large financial structure, income inequality "stabilizes across agents", but savings declines and output converges. In other words, at lower levels of development financial sector growth aids the rich and therefore increases inequality, but at high levels it aids all income levels thus lowering it.

Considering a lower section of the hypothetical inverted-U curve, Beck et al. (2004) provide empirical evidence that financial development decreases income inequality while disproportionately aiding the relatively poor.

An alternative theory considers the level of credit as the mechanism through which income inequality affects output volatility. Iyigun & Owen (2004) argue that if there is abundant credit, whereby only the poorest cannot obtain it, then increases in income inequality increase the variance in consumption and output. On the other hand, if credit is limited to the point that only the wealthiest can obtain it, increases in income inequality lower the volatility of consumption and output. This would hold, they suggest, if per capita income is high, as observed in the US.

This paper considers neither consumption nor output growth. It does include a measure of household credit in its set of variables in addition to its interest rate. The two variables of interest will be US income inequality and its financial sector's relative size, comparable to financial development.

The rest of the paper is organized as follows: Section 2 describes the CVAR model and hypotheses on cointegrating relations; Section 3 discusses the VECM methodology and the corresponding MA and structural forms, as related to the structural VAR model, while proposing possible orderings of the series vector; Section 4 describes the data and variables used; Section 5 presents unit root testing results while Section 6 performs a univariate analysis of two of the variables (financial sector size and household credit); Section 7 considers the unrestricted VAR model in VECM form (not to be confused with the UVAR model analyzed in Section 10), with Section 8 addressing misspecification testing of the CVAR model and Section 9 considering long-run and short-run identification; Section 10 examines the unstructured VAR, or UVAR, model and includes impulse response analysis; Section 11 focuses of the structural VAR and causality ordering in both short-run and long-run restriction testing; finally, Section 12 considers a factor analysis of inequality measures and Section 13 concludes. An Appendix contains many additional figures, tables and estimation results.

2 Model

Few economic models exist as a template for postulating long-run relationships between inequality and financial sector size. Consider a simple bivariate model from Assa (2012)

$$\Gamma_t = \alpha + \beta_1 \phi_t + \varepsilon_t \tag{1}$$

where Γ_t is the Gini coefficient and ϕ_t is the financial, insurance, and real estate sectors' value added to GDP. Of course any inference from such a simple representation will be quite weak. Aside from exogeneity assumptions, our interpretation presumes a static environment, a *ceteris paribus* condition which does not resemble the non-recurring changes over time observed empirically.

I therefore reject the *specific-to-general* model specification in favor of a *general-to-specific* approach as advocated by Haavelmo, Hendry, Sims, Juselius and others. This will allow me to first specify a statistical model of the data and its representations, and then test whether various theoretical models can be explained by the observed data.

I will specify a cointegrated VAR (CVAR) model to estimate stationary long-run relationships (possible equilibria) and short-run responses between the size of the US financial sector (value added as share of GDP), income inequality (measured as the top 0.01%'s share of income), household credit, and an interest rate (US 10-year constant maturity bond). The vector error correction model (VECM) form is

$$\mathbf{\Delta x_t} = \mathbf{\Pi \tilde{x}_{t-1}} + \sum_{i=1}^{k-1} \mathbf{\Gamma_i \Delta x_{t-i}} + \Phi \mathbf{D_t} + \mu + \varepsilon_\mathbf{t} \tag{2}$$

where $\mathbf{\tilde{x}_{t-1}} = \begin{pmatrix} top001inccg \\ efinshv \\ finfhh \\ govBr \end{pmatrix}$, $\mathbf{\Pi} = \alpha\tilde{\beta}'$ such that $\tilde{\beta}'$ is a vector of long-run cointegrating relations, and Γ is a matrix of short-run structures. Additionally, $\mathbf{D_t}$ is a vector of dummy variables and μ an intercept term. I assume $\varepsilon_t \sim N_p(0, \Omega)$, where p equals the dimension of the vector $\mathbf{x_t}$. Of course the final specification will depend on the significance of any structural breaks in the data and whether or not such breaks (or any other deterministic components) should also be included in the cointegrating space or not.

Two possible cointegrating relationships are hypothesized , each of which will be tested within the CVAR framework.

$$\mathcal{H}_0 : \qquad a_1 top001inccg + a_2 efinshv + a_3 finfhh \sim I(0)$$

$$\mathcal{H}_1 : \qquad b_1 top001inccg + b_2 efinshv + b_3 govBr \sim I(0)$$

where a_i and b_i represent coefficients of cointegrating vectors β_1^c and β_2^c. The CATS for RATS software will be utilized for estimation and hypothesis testing, in addition to OxMetrics. The latter will become necessary for joint hypothesis testing of both the alpha and beta vectors once the model is identified.

These relationships will also be analyzed using the UVAR and SVAR models in order to describe possible impulse responses and sequences of causality, respectively. Further research, however, will focus on the CVAR model in order to infer any possible long-run equilibrium between income inequality, financial sector size, interest rates, and household credit, and the short run adjustment mechanisms back to equilibrium after a shock. Other annually measured variables to consider (which would then correspond to inequality measurement frequencies) might be the output gap, household leverage, private sector leverage, and wealth inequality (though this is a more challenging variable to measure for longer time series analysis).

3 Methodology

Much of the CVAR model's appeal lies in its flexibility. By rewriting the model using the Granger Representation Theorem, I can impose a structural form on the model, identify it, and thus evaluate impulse responses based on stochastic shocks. The MA representation of the underlying VAR model from equation (2) is given by:

$$\mathbf{x_t} = \mathbf{C}\sum_{i=1}^{t}\varepsilon_i + \mathbf{C}^*(L)\varepsilon_t + \tilde{\mathbf{X}}_\mathbf{0} \tag{3}$$

where $C = \beta_\perp(\alpha'_\perp\Gamma\beta_\perp)^{-1}\alpha'_\perp = \tilde{\beta}_\perp\alpha'_\perp$. I can rewrite the underlying VAR from equation (2) as a structural VAR (in error correction form) with a non-singular matrix $\mathbf{B}$:

$$\mathbf{B\Delta x_t} = \tilde{\alpha}\tilde{\beta}'\tilde{\mathbf{x}}_\mathbf{t-1} + \sum_{i=1}^{p-1}\tilde{\Gamma}_i\Delta x_{t-i} + \tilde{\Phi}\mathbf{D_t} + \mathbf{u_t} \tag{4}$$

where $\tilde{\Gamma_i} = \mathbf{B}\Gamma_i$, $\tilde{\alpha} = \mathbf{B}\alpha$, $\tilde{\Phi} = \mathbf{B}\Phi$, $u_t = \mathbf{B}\varepsilon_t$, and $u_t \sim IN_k(0, \Sigma)$, where $\Sigma = \mathbf{B}\Omega\mathbf{B}'$. I can also decompose the C matrix from the MA form by postmultiplying by $\mathbf{B}^{-1}$ such that $\tilde{C} = C\mathbf{B}^{-1} = \tilde{\beta}_\perp\alpha'_\perp\mathbf{B}^{-1}$, where the r zero columns represent transitory shocks and the $p - r$ nonzero columns represent permanent shocks. Thus the structural MA form is:

$$\mathbf{x_t} = \tilde{\mathbf{C}}\sum_{i=1}^{t}u_i + \tilde{\mathbf{C}}^*(L)u_t + \tilde{\mathbf{X}}_\mathbf{0} \tag{5}$$

Note that the structural MA form of the CVAR model corresponds to the following structural VAR model, using the same $\mathbf{B}$ ordering matrix! Note that the Γ coefficient matrices in equation (6) do not correspond to those in the above equations.

$$\mathbf{BX_t} = \mathbf{\Gamma_0} + \mathbf{\Gamma_1 X_{t-1}} + \mathbf{\Gamma_2 X_{t-2}} + \varepsilon_\mathbf{t} \tag{6}$$

Identifying the system requires imposing $p(p-1)/2$ restrictions with the aim of the empirical shocks satisfying the property that $u_t' \sim IN(0, I)$, where u_t is composed of both transitory and permanent shocks.

Given that income inequality and financial development, or financial sector size, have a theoretically nonlinear relationship, there are multiple ways of ordering the imposed causality in **B** when identifying the model as a recursive system. For example, Greenwood & Jovanovic (1990) suggest in a country with low per capita income and low growth, financial sector growth (and its growing intermediary infrastructure) aid rich households disproportionately and increases income inequality. Both also cause an increase in household credit. Beck et al. (2004) argue the opposite, that increased financial development in low income countries decreases income inequality and disproportionately helps the poor. In both, however, the implied theoretical causality runs from financial development to income inequality. The level of household credit, however, can be considered either to be causing the sign of the coefficient on income inequality or itself being affected by financial sector size, thus $finfhh$ will be ordered before and after.

Estimates from the CVAR model suggest long-run exclusion of the interest rate $govBr$ from the model, concluded by further empirical testing, and so it will be ordered first by its superior exogeneity. These hypotheses will all be tested in the standard SVAR model.

4 Data

4.1 Income Inequality

The variable $top001inccg$ represents the top 0.01%'s share of income in the US, including capital gains. This measure is chosen because I consider the financial sector size in the analysis and capital gains are mostly derived from the financial sector. Notice in Figure 1 (plotting levels and differences) how $top001inccg$ is amplified during financial booms. The top percent of the top percentile is chosen because Piketty & Saez (2006) cite the effect that the highest incomes have on the overall distribution of income–theyfluctuate much more than the lower majority. Data is available in annual observations for 1913-2012 from **?**, available on their data website (http://topincomes.g-mond.parisschoolofeconomics.eu/, accessed 19/10/2013).

Additionally, other measures of US income inequality from the same Piketty & Saez data set include the top 1% and top 0.1%'s share of income ($top1inc$ and $top01inc$, respectively) both including and excluding capital gains ($top1inccg$ and $top01inccg$). I have also collected a Pareto-Lorenz coefficient series which measures the distribution of incomes, not simply a percentile's share. These will be considered in a factor analysis exercise in Section 12 and their plots are all included in the Appendix, Section A.

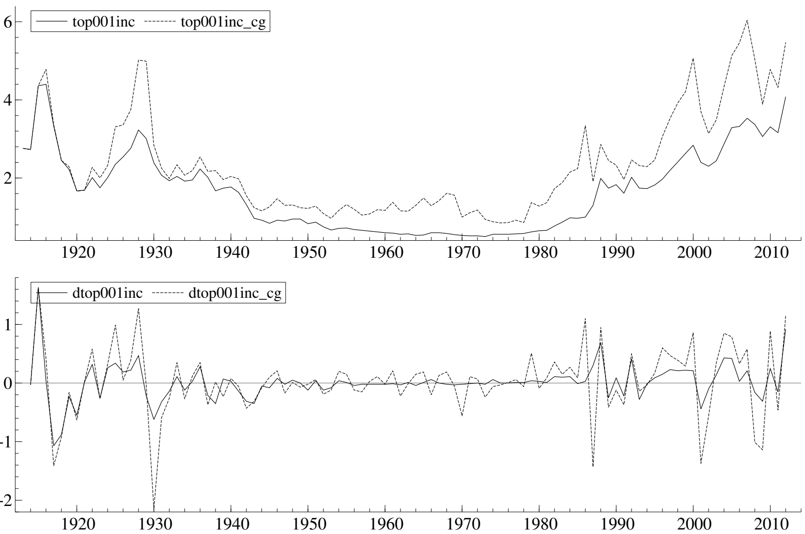

Figure 1: Top 1% Share of Income (incl. Capital Gains)

4.2 Financial Sector

4.2.1 Financial Sector Size

The variable $efinshv$ represents the financial sector's share of GDP, as measured by value added. The data is sourced from **?** "Has the US Financial Industry Become Less Efficient", from the author's personal website (

http://pages.stern.nyu.edu/ tphilipp/research.htm), thus I retain his variable name for consistency.

Annual observations exist for 1859-2009.

4.2.2 Household Credit

Another variable, $finfhh$, measures total debt flow to households, scaled by GDP. This data series is also from **?**, therefore I again retain his variable name for consistency. Annual observations exist for 1861-2011. This variable is an important parameter in the theoretical model as Iacoviello (2008) has shown a historical link between increasing household debt and increasing income inequality.

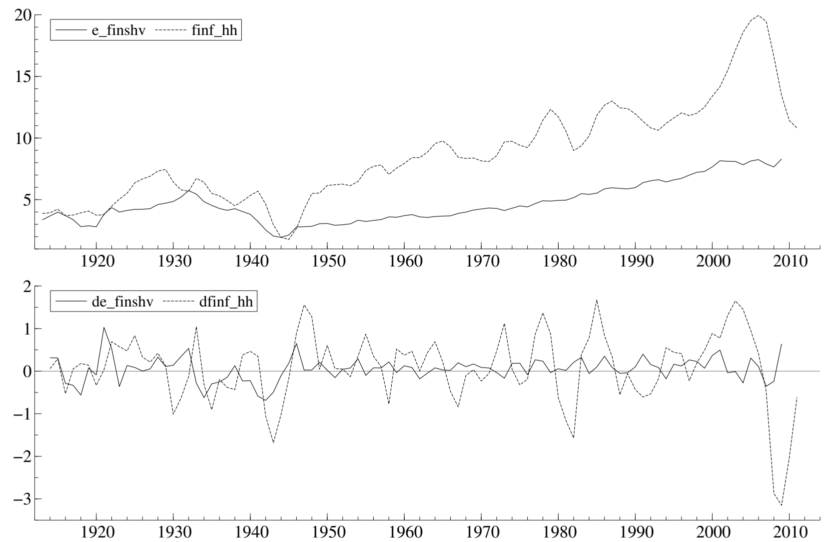

Figure 2: Financial Sector Value Added and Household Flow of Debt, both Share of GDP

4.3 Lending (Interest) rates

I use two interest rate series from the Global Financial Data (GFD) database. The first,$corpBr$, is a series of Moody's Corporate AAA Yield, or MOCAAAD from the GFD. The original monthly data contains average opening and average closing per annum rates. I have taken the average of the monthly open and close rates, and then taken the annual average of this in order to annualize the series. I have performed the same transformation for the second series $govBr$, the USA 10-year Bond Constant Maturity Yield, or IGUSA10D from the GFD. Thus both series are available for 1913-2012 observations. Both series are plotted in levels and differences in Figure 3. I ultimately use $govBr$ in the model.

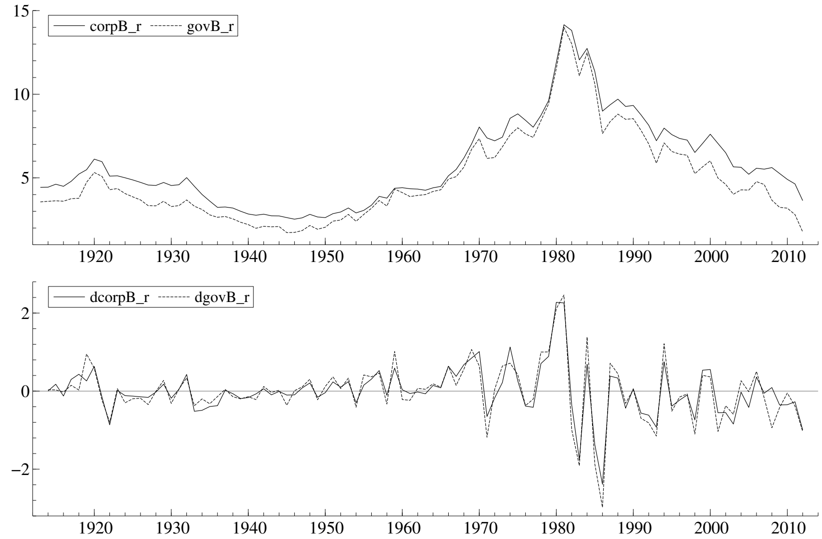

Figure 3: Moody's AAA Corporate Bond Yield and US 10-year Bond Yield

5 Unrestricted VAR Model

Though I have collected several data series which measure both the interest rate and income inequality, I initially choose a vector of variables including $top001inccg$ and $govBr$, as well as our financial sector and household credit measures $efinshv$ and $finfhh$, based on its lack of autocorrelation in the lag determination and in the residuals after estimating the unrestricted model. (Future analysis can determine robustness of the finding by testing the model with alternate income inequality variables and interest rates.)

5.1 Lag Length Determination

I use a number of measures to determine the lag length k in our unrestricted VAR(k) model in VECM form

$$\Delta \mathbf{x_t} = \mathbf{\Pi x_{t-1}} + \sum_{i=1}^{k-1} \mathbf{\Gamma_i \Delta x_{t-i}} + \mathbf{\Phi D_t} + \mu + \varepsilon_\mathbf{t} \qquad \forall t = 1, \ldots, T \tag{7}$$

where $\mathbf{x_{t-1}} = \begin{pmatrix} top001inccg \\ efinshv \\ finfhh \\ govBr \end{pmatrix}$ and $\varepsilon_t \sim iidN_p(0, \Omega)$. The vector $\mathbf{D_t}$ is comprised of dummy variables to be specified in Section 8.1.1. It is important to note that the significance of using information criteria or likelihood ratio tests to specify the model's lag length is dependent on the rest of the model being correctly specified, i.e. shifts and nonconstant parameters are all taken into account. Of course the underlying goal is to specify a model which is a statistical representation of the data such that our underlying multivariate normality assumption of the disturbance term holds.

In STATA I test our initial vector by increasing lag length incrementally (Table 4). The results strongly suggest a lag length of two for the unrestricted model. In CATS for RATS, I estimate

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-634.22914				39.081619	15.017156	15.063392	15.132104
1	-243.0206	782.41707	16	3.57e-156	.00572883	6.1887201	6.4198972	6.7634616
2	-185.2623	115.5166	16	3.979e-17	.0021503*	5.2061719*	5.6222906*	6.2407065*
3	-173.57827	23.36806	16	.10424406	.00239563	5.3077241	5.9087845	6.8020519
4	-160.00798	27.140589	16	.03994673	.00256768	5.3648936	6.1508958	7.3190146
5	-144.57384	30.86827	16	.01398694	.00265437	5.3782081	6.3491519	7.7921223
6	-134.79462	19.558456	16	.24076895	.00316587	5.5245792	6.6804647	8.3982866
7	-128.95915	11.670935	16	.76630462	.00419531	5.7637447	7.1045718	9.0972452
8	-120.84557	16.227161	16	.43722216	.00535182	5.9493075	7.4750763	9.7426012
9	-105.95429	29.782564	16	.01916288	.00593323	5.975395	7.6861055	10.228482
10	-94.229842	23.448888	16	.10225145	.00725571	6.0759963	7.9716485	10.788876
11	-82.013177	24.433329	16	.08045808	.00903033	6.1650159	8.2456098	11.337689
12	-64.057638	35.911078	16	.00297685	.0101835	6.1190032	8.3845388	11.75147

Table 1: Lag Length Determination for Vector [top001inccg efinshv finfhh govBr]' (STATA)

the unrestricted model (equation 9) with an initial lag $k = 2$, and then utilize the lag length determination function. The first result provides us with incremental lag reduction test results (Table 5). Importantly, I consider the LM tests for first order and k'th order autocorrelation.

While the lag determination by information criteria in CATS suggests $k = 2$, I reject the null of no first order autocorrelation though I fail to reject k'th order autocorrelation, both at the 5% level. The VAR(7) model most strongly supports no first order autocorrelation and the VAR(5) model

Model	k	T	Regr	Log-Lik	SC	H-Q	LM(1)	LM(k)
VAR(8)	8	89	33	364.746	-1.539	-3.743	0.017	0.297
VAR(7)	7	89	29	356.610	-2.163	-4.100	0.272*	0.298
VAR(6)	6	89	25	350.388	-2.830	-4.500	0.107	0.867
VAR(5)	5	89	21	340.642	-3.418	-4.820	0.033	0.931*
VAR(4)	4	89	17	325.907	-3.894	-5.029	0.002	0.210
VAR(3)	3	89	13	314.604	-4.447	-5.315	0.005	0.162
VAR(2)	2	89	9	303.136	-4.996*	-5.597*	0.041	0.088
VAR(1)	1	89	5	247.264	-4.548	-4.882	0.000	0.000

Table 2: Lag Length Determination (CATS)

most strongly supports no k'th order autocorrelation, so there may be something happening in later periods that the unrestricted model does not capture.

The second result (Section B, Table 12 in the Appendix) presents a series of lag reduction tests using LR tests, where the null hypothesis is if VAR(j) can be restricted to a VAR(i), where $i < j$. (P-values are shown in brackets.)

Overall, I find that the information criteria suggests $k = 2$ and the LM tests for autocorrelation suggest $k = 7$ and $k = 5$ depending on first and k'th order, respectively. Similarly, the lag reduction tests suggest I cannot impose restrictions from VAR(5) to VAR(4), though I can restrict from VAR(4) to VAR(3) and from VAR(3) to VAR(2). When faced with such conflicting results, Juselius (2006) suggests the significance of larger lags may be due to misspecification of the model, wherein the omission of dummies and mean shifts is likely to generate autocorrelated residuals. Thus I will consider lag length determination together with specifying deterministic components in the following section.

6 Misspecification Testing

By following the Johansen method, I began my estimation procedures with the unrestricted VAR model and continue with the critical misspecification tests. As Johansen emphasizes, the aim is to find a valid statistical specification of the data through repeated misspecification tests such that inference is possible, and significant.

Initially testing the VAR(2) unrestricted model in the specification process, I test our disturbance term normality assumption with the residuals by each single equation and the entire system using PcGive in OxMetrics (Table 6). I reject the null of normality in the system and in each single equation, except for $finfhh$, which I fail to reject. The more detailed residual testing from CATS (Table 8), which otherwise confirms the test statistics from PcGive, shows skewness in $efinshv$ and ARCH. Juselius (2006) suggests greater concern for skewness than kurtosis, which the model is quite robust in handling. Autocorrelation, however, is not strongly prevalent in the unrestricted model and I reject first and second order autocorrelation.

Variable	Dist.	Test stat.	p-value
top001inccg	$\chi^2(2)$	25.854	[0.0000]**
efinshv	$\chi^2(2)$	9.1166	[0.0105]*
finfhh	$\chi^2(2)$	0.0563	[0.9723]
govbr	$\chi^2(2)$	35.364	[0.0000]**
Vector	$\chi^2(8)$	70.301	[0.0000]**

Table 3: Normality Testing Using Reduced-form Residuals (PcGive)

Tests for Autocorrelation				
LM(1):	ChiSqr(16)	=	11.062	[0.806]
LM(2):	ChiSqr(16)	=	17.083	[0.380]

Table 4: Residual Analysis

	Mean	Std.Dev	Skewness	Kurtosis	Maximum	Minimum
DTOP001INCCG	-0.000	0.504	0.195	5.748	1.747	-1.619
DEFINSHV	-0.000	0.243	0.496	4.491	0.930	-0.581
DFINFHH	-0.000	0.503	-0.055	2.761	1.308	-1.329
DGOVBR	0.000	0.689	0.199	6.451	2.401	-2.683

	ARCH(2)		Normality		R-Squared
DTOP001INCCG	8.282	[0.016]	25.854	[0.000]	0.180
DEFINSHV	1.524	[0.467]	9.117	[0.010]	0.224
DFINFHH	0.313	[0.855]	0.056	[0.972]	0.621
DGOVBR	20.215	[0.000]	35.364	[0.000]	0.124

Table 5: Residual Analysis of Unrestricted Model (CATS)

6.1 Deterministics

I proceed in identifying outlier observations and shocks to the VECM model (equation 8), with $k = 2$, paying close attention to the previously suggested structural breaks in the univariate analysis–namely, $top001inccg$ in 1974 (based on $top001inc$), $finfhh$ in 1934 and 1988, and $govBr$ in 1978.

6.1.1 Outliers and Dummy Variables

To construct dummies, I examine the largest standardized residuals for our unrestricted VECM model. I consider residuals that are greater than 2.75 standard deviations from the mean and create the set of pulse (p) or transitory (t) dummies in Table 9 based on the behavior of the residuals.

Variable	Dummy	Year	Standardized Residual
$top001inccg$	dum15p	1915	3.451
	dum28t	1928, 1930	3.097, -3.198
	dum01p	2001	-2.872
$efinshv$	dum21p	1921	3.815
$govBr$	dum80p	1980	2.764
	dum81p	1981	3.466
	dum86p	1986	-3.873

Table 6: Dummy Variable Specifications for equation (8)

Note that there are no dummies for $finfhh$ because I failed to reject univariate normality in its residuals above. Having included the dummies in the unrestricted model estimate, I now fail to reject normality in the system with a $\chi^2(8) = 8.134$ test statistic and p-value of 0.421. The theoretical assumption of normally distributed errors appears to hold, aiding later statistical inference. (See Appendix Section D for detailed test results.)

6.1.2 Structural Breaks

Whereas I previously considered univariate structural breaks, I now examine the entire system. I specify an unrestricted constant term and allow for trends in the levels and a non-zero mean in the cointegration relations. However, restricting the trend to the cointegration space means a trend in the cointegration space may exist as it is not canceled out by any trend in the levels. The question is, does this trend change at any point?

From forward recursive testing of the eigenvalues and cointegrating relations there is some non-constancy prevalent in the system, but it is difficult to discern if there exists a full structural break or level shift. (See the recursive testing plots in the Appendix, Section G, Figures 28-30.) To test if any possible shifts are occurring after the end of WWII, which the eigenvalue and alpha vector plots suggest, I estimate the unrestricted model with a single shift dummy (or break in levels in CATS) at each year from 1945 to 1950. Each of these dummies, however, are found to be long-run excludable in likelihood-ratio testing (results below) because as a shift dummy it is included in the cointegrating space. Based on the plots of the beta vector's parameter constancy, I also test for a structural break in 1987, one year after our a pulse dummy $dum86p$. I fail to reject the null that its beta coefficient is zero do not include and break in the system.

Test of Variable Exclusion		
Break Date	LR-Test of Exclusion	p-value
1946:01	0.273	[0.602]
1947:01	0.328	[0.567]
1948:01	0.180	[0.672]
1949:01	0.218	[0.641]
1950:01	0.366	[0.545]
1987:01	2.388	[0.122]

Note: $\chi^2(1)$ CV because assuming $r = 1$ as later determined.

Table 7: Structural Break Testing of System Using Shift Dummies (CATS)

6.2 Specified VECM

I accept the specified vector error correction, or CVAR, model below with $k = 2$ after failing to reject normality in the vector model with a p-value of 0.4205.

$$\mathbf{\Delta x_t} = \mathbf{\Pi \tilde{x}_{t-1}} + \sum_{i=1}^{k-1} \mathbf{\Gamma_i \Delta x_{t-i}} + \mathbf{\Phi D_t} + \mu + \varepsilon_\mathbf{t} \tag{8}$$

where $\mathbf{\tilde{x}_{t-1}} = \begin{pmatrix} top001inccg \\ efinshv \\ finfhh \\ govBr \\ t \end{pmatrix}$, $\mathbf{\Pi} = \alpha\tilde{\beta}'$, $\tilde{\beta} = \begin{pmatrix} \beta \\ \beta_1 \end{pmatrix}$, and $\varepsilon_\mathbf{t} \sim iidN_p(0, \Omega)$. Vector $\mathbf{D_t}$ contains the seven dummies specified above in Table 9 and μ is an intercept term.

The unrestricted estimation results for the unrestricted model are presented in Section C of the Appendix. Plots for each residual series in the specified model are presented in Section E of the Appendix, which include actual and fitted values of Δx_t, standardized residuals, autocorrelations, and histograms of the standardized residuals with Kolmogorov-Smirnov and Jarque-Bera test statistics for normality.

6.3 Cointegration Rank

I consistently find a cointegration rank of $r = 1$ for the VECM model, specifically using the Bartlett Correction estimates that correct for finite sample bias–I use these values given our effective sample size of only 95 observations. (The values below are simulated critical values. The original, biased values are provided in the Appendix Section F.) Interpreting the results is like a simple likelihood ratio test, one that distinguishes between eigenvalues that correspond to stationary versus non-stationary relations. That is, I test the restricted model with rank r $\mathcal{H}(r)$ against the general full rank model $\mathcal{H}(p)$, where $p = 4$. Reading the test results from top to bottom, I reject no restrictions however $r = 1$ is accepted for the corrected values. To discern the appropriate rank, I examine the roots of the companion matrix (see Table 15 and Figure 25 in the Appendix, Section F). The

I(1)-ANALYSIS							
p-r	r	Eig.Value	Trace	Trace*	Frac95	P-Value	P-Value*
4	0	0.336	81.894	75.298	63.271	0.001	0.003
3	1	0.210	42.960	40.313	42.538	0.043	0.080
2	2	0.112	20.615	18.368	25.932	0.201	0.326
1	3	0.094	9.360	7.175	12.380	0.160	0.328

Note: * denotes finite sample Bartlett corrected value.

Table 8: Rank Trace Test Statistics (CATS)

second highest root has a modulus of 0.925, and its cointegrating relation does not appear very stationary either. Thus I claim $r = 1$ cointegrating relations and $p - r = 3$ unit roots (or common stochastic trends) in the specified VECM.

The unrestricted model estimates with a rank of one imposed are included in the Appendix, Section I.

7 CVAR Identification

7.1 Long-Run Relations

Given the cointegration rank of one, I test both hypotheses of the cointegrating relationships specified in Section 2. First, $\mathcal{H}_0$ considered a cointegrating relationship between income inequality ($top001inccg$), financial sector size ($efinshv$) and household credit ($finfhh$). This null hypothesis cannot be rejected with a p-value of 0.751 (see Appendix, Section J), and implies the following cointegrating relation:

$$\beta_1^c \mathbf{x_t} = top001inccg - 1.675efinshv + 0.522finfhh = 0 \tag{9}$$

This result suggests a significant long-run comoving relationship between income inequality and financial sector size. Given the importance of the financial sector to the fraction within the top percentile of incomes measured here, this result is not particularly surprising. At the same time, income inequality is inversely related to household credit. This also is not surprising, given that credit is likely to alleviate the symptoms of income inequality and therefore decrease it.

My second hypothesis, $\mathcal{H}_1$, considered a cointegrating relationship between income inequality ($top001inccg$), financial sector size ($efinshv$) and the interest rate ($govBr$). Given, the exogeneity of the interest rate in our model, I do not find a significant relationship.

7.2 Short-Run Relations

Two additional properties of the decomposed Π matrix are considered and tested: weak exogeneity and a unit vector in the alpha matrix. In the ECM form, weak exogeneity implies that a variable is not adjusting to the cointegrating relation at all–i.e. it does not error correct. This is equivalent to the MA (or Granger) representation form having a unit vector in alpha, or that the coefficient is purely adjusting and therefore only contains transitory effects on the model. Notice the properties are in fact reciprocals of each other between the two forms of the model. The test statistics are summarized in Tables 16 and 17 in Section H of the Appendix.

Focusing on $r = 1$, I fail to reject the null that either $efinshv$ and $govBr$ are weakly exogenous, in the ECM form, and thus the common stochastic trends in the model are given by cumulated shocks to financial sector size as well as the government bond rate. This implies that the financial sector size and government bond rate variables are both purely pushing the system in a long-run trend and not pulling it back from disequilibrium. At the same time I fail to reject that $finfhh$ has a unit alpha vector. Therefore shocks to household credit are purely adjusting to the long-run equilibrium implying household credit only has a transitory effect in the model–it only pulls the system back to equilibrium after a shock.

Note, however, that all of the above results are individual tests. Therefore I jointly test these hypotheses below in PcGive (I cannot test them all jointly in CATS unfortunately) and fail to reject the null that $efinshv$ and $govBr$ are weakly exogenous and $finfhh$ is a unit vector in alpha and is jointly significant.

log-likelihood	-168.718074	-T/2log|Ω|	370.478568
no. of observations	95	no. of parameters	54
rank of long-run matrix	1	no. long-run restrictions	2

beta is identified			p-value
LR test of restrictions	$\chi^2(2)$	4.2925	[0.1169]

I do, however, reject the joint weak exogeneity in the restricted model at the 1% level (Bartlett corrected $\chi^2(4) = 16.637$, p-value = 0.002), while still failing to reject a unit vector in alpha for household credit at the 5% level ($\chi^2(3) = 7.775$, p-value = 0.051).

7.3 MA Representation

Following the methodology in Section 3, I estimate the Moving Average form of the restricted VECM (also known as the Granger Representation), or equation (3). See estimation results in the Appendix, Section K.

The interpretation of the $p-r = 3$ common stochastic trends is largely dependent on the normalization pattern of the vectors. I follow the CATS procedure of normalizing on the largest value. This normalization pattern suggests one possible interpretation of the $\alpha'_{\perp}$ matrix (Appendix, Section K) is the following:

1. CT(1): Shocks to the interest rate, which I found to be exogenous, have a positive, large, though not entirely significant effect on household credit.
2. CT(2): Shocks to income inequality have a significant, and negative, effect on household credit.
3. CT(3): Shocks to the size of the financial sector have a positive, though small and insignificant effect on household credit.

Examining long-run impact matrix **C**, which defines the permanent effects on each of the variables from shocks to each of the variables, I find the following significant effects.

Column-wise inspection shows that **cumulated empirical shocks to**:

1. income inequality ($top001inccg$) have a strongly negative and significant effect on household credit ($finfhh$) and itself;
2. the size of the financial sector ($efinshv$) have a positive, significant effect on income inequality and an even greater and significant effect on household credit, and itself;
3. household credit have positive and significant effects on the interest rate ($govBr$) and itself;
4. the interest rate have a small but positive and significant effect on income inequality.

Row-wise inspection of coefficients shows that, **over time**:

1. income inequality has been most significantly, and positively, impacted by its own shocks, those to financial sector size, and the interest rate;
2. financial sector size has been most significantly affected by its own shocks only;
3. household credit has been positively and significantly impacted by financial sector size but negatively impacted by income inequality;
4. the interest rate has most significantly impacted itself.

These observations reinforce some of the earlier results: that income inequality is positively comoving over time with the size of the financial sector; that household credit is also comoving with financial sector size; and that the interest rate (or government bond yield) is largely exogenous.

7.4 Structural MA Form

I also estimate the structural MA form of the CVAR model. (See Appendix Section L for all results.) Note that the impulse response functions slowly converge to the **C** matrix, the long-run permanent effect. One value of using the structural MA form is that the long run impact matrix, **C**, can be decomposed into its transitory and permanent effects.

Given our rank of 1, this implies $p - r = 3$ permanent linear combinations of the structural shocks have permanent effects. These are the cumulated long-run stochastic trends, in other words.

Ordering of the shocks matrix in Structural MA model follows

	L_1	L_2	L_3
TOPOO1INCCG	*	*	*
EFINSHV	*	*	0
FINFHH	*	*	*
GOVBR	*	0	0

(I will later test a similar sequence of proposed causality in the SVAR model as Orders 2 and 3.) Thus examining the **B** matrix (Appendix, Section L.1), I can interpret the first permanent trend as being caused by shocks to the interest rate, the second permanent trend as being caused by shocks to financial sector size, and the third permanent trend begin caused by shocks to income inequality. The single transitory effect is caused by a shock to financial sector size.

The impulse responses for the above shocks are plotted in the Appendix, Section L.2. As expected, the variables all converge to zero from a transitory shock in the first column of plots. The remaining plots for the permanent effects are mainly suggestive, as CATS does not provide confidence intervals around the functions. Thus I focus on the simplified impulse responses in the UVAR model, which are shown with confidence bands to discern significance.

8 Unstructured VAR Model

As an exercise I now consider a UVAR model of the system described above. For consistency I retain the same variable ordering in the vector as in the CVAR model, and I continue with the specified lag-length ($k = 2$) and dummy variables created above. The UVAR(2) model is

$$\mathbf{X_t} = \mathbf{A_0} + \mathbf{A_1}\mathbf{X_{t-1}} + \mathbf{A_2}\mathbf{X_{t-2}} + \mathbf{e_t} \tag{10}$$

where $\mathbf{X_t} = \begin{pmatrix} top001inccg \\ efinshv \\ finfhh \\ govBr \end{pmatrix}$, $\mathbf{e_t} \sim iid(0, \Sigma)$, and $\mathbf{A_0}$ includes all the dummy variables and a constant. Note that I do not include the first-differenced, stationary series in this model. I follow the Enders (1995) argument that

> Sims (1980) and others, such as Doan (1992), recommend against differencing *even if the variables contain a unit root.* They argue that the goal of VAR analysis is to determine the interrelationships among the variables, *not* the parameter estimates (p.301).

Thus not wanting to "throw away" information concerning the comovements of the variables, I do not first-difference the series (just like in the VECM estimation above.)

Testing for joint residual normality (using Cholesky orthogonalization), I fail to reject normality in the skewness, kurtosis, and Jarque-Berra test with p-values of 0.9678, 0.5602, and 0.8683, respectively. The specification of the VECM form performs equally well in the UVAR form, if not better.

The variance decomposition of the estimated model is included in the Appendix, Section M. As is typical of forecast error variance decomposition, the estimated variable's share of the error declines over time. Thus the income inequality variance is increasingly composed of the errors from financial sector size and the two converge over time. Similarly, the forecast error variance of household credit is increasingly composed of the variance from financial sector size.

8.1 Granger Causality

Before testing the VAR system for Granger causality I simply test each pair of vectors to provide a basis of comparison. (The results are presented in Table 18 in the Appendix Section N.) At 1% significance I find $efinshv$ Granger causes $finfhh$ and that $govBr$ Granger causes $finfhh$. At 5% significance I find that $efinshv$ Granger causes $top001incgc$ and also that $finfhh$ Granger causes $efinshv$. Because household credit is an important component of overall financial sector size, the latter results should not be very surprising. The finding of financial sector size Granger-causing income inequality, however, is a result consistent with the theoretical hypothesis of the paper.

In the VAR Granger causality test I fail to reject that individual excluded variable $govBr$ Granger causes $finfhh$ as determined in the pairwise test, while the block exogeneity tests of the VAR system all reject the null of no Granger causality at the 1% significance level, except for the vector impacts on $finshv$–which is nearly significant with a p-value of 0.0148 (Appendix Section N, Table 19).

8.2 Impulse Response Functions

Impulse response functions are calculated for the UVAR model as responses to a Cholesky one standard deviation innovation at time zero (Appendix, Section O). By column from left to right, the figure plots impulse responses for each variable from shocks to $top001inccg$, $efinshv$, $finfhh$, and $govBr$, respectively. There appear to be several significant responses in this simple exercise. First, financial sector size shocks ($efinshv$) cause $top001inccg$ to remain significantly positive for the entire duration of the response period (10 years), that is a significant increase in inequality. Significance in the reciprocal shock, income inequality on financial sector size, is not observed. Because the inequality measure includes capital gains the result makes intuitive sense. (In fact$top001inccg$ is amplified in the levels plots during peaks, and then falls precipitously during busts.) The same is true for $finfhh$. It stays significantly positive until the final period.

The second important finding is that the interest rate ($govBr$) remains significantly positive, though narrowly so, from a shock to $finfhh$. Interestingly, this contradicts the above finding that $govBr$ Granger causes $finfhh$. I will consider both when testing various ordering of the vector in the SVAR model in the next section.

9 Structural VAR Model

Whereas the above UVAR(2) model was a reduced form system like the CVAR model before it, I now consider an SVAR model. As shown in the CVAR model, any identification of long or short-run parameters requires imposing restrictions, and only over-identifying restrictions may be tested for significance using a likelihood ratio test. However, I now pay particular attention to the contemporaneous effects any shocks may have on the other variables in the system and impose a structural form on the contemporaneous coefficient matrix. Note that each of the orderings below, again, do not contain the first-differences of each series, per my adherence to Sims' original philosophy of the VAR method.

I begin with the initial ordering of $\mathbf{X_t}$, before considering alternative variations of contemporaneous effects in the model. The SVAR(2) model then becomes

$$\mathbf{BX_t} = \mathbf{\Gamma_0} + \mathbf{\Gamma_1 X_{t-1}} + \mathbf{\Gamma_2 X_{t-2}} + \varepsilon_\mathbf{t} \tag{11}$$

where $\mathbf{X_t}$ is exactly the same as in equation (11), and $\varepsilon_t \sim iid(0, \Sigma_\varepsilon)$. Of interest throughout this section will be the implications of the identifying restrictions imposed on the $n \times n$ matrix $\mathbf{B}$. (Note that the Γ matrices specified here are not the same as in the VECM form.)

9.1 Short-Run Restrictions

I construct several short-run restrictions to test in the SVAR model. Because of the Cholesky decomposition, I must impose six restrictions on $\mathbf{B}$ to exactly identify the model. (Recall that from the UVAR estimates I have 10 known parameters from the covariance matrix of the residuals and in the SVAR model I have 16 unknown parameters–four from the unknown diagonal elements of the covariance matrix and 12 from the contemporaneous relations in the $\mathbf{B}$ matrix.)

A recursive system results through the Cholesky decomposition, thus the ordering of the variables in the vector $\mathbf{X_t}$ implies causality and affects the impulse responses. I compare four unique orderings in comparing impulse responses. The orderings are as follows:

Sequence	Order 1	Order 2	Order 3	Order 4
1	$top001inccg$	$govBr$	$govBr$	$finfhh$
2	$efinshv$	$efinshv$	$efinshv$	$govBr$
3	$finfhh$	$top001inccg$	$finfh$	$efinshv$
4	$govBr$	$finfhh$	$top001inccg$	$top001inccg$

Order 1 simply follows the initial ordering from the CVAR estimates. Orders 2 and 3 both take into account significant exogeneity of $govBr$ and also follow the literature in considering interest rates to be exogenous relative to the other variables in the model. Both suggest that contemporaneous causality flows from financial sector size, which itself is determined by the price of money ($govBr$) to income inequality, while distinguishing by the amount that household credit influences this. The last ordering, Order 4, acknowledges findings from the UVAR model estimates that interest rates are significantly impacted by household credit. Additionally, this takes into account the theory that the impact of financial development on income inequality is dependent on the level of credit constraints.

Impulse response results are presented in the Appendix, Section P.1. Cholesky identification restrictions do not change the impulse responses significantly in Order 1, compared to the UVAR model. Most significantly, I find that shocks to financial sector size still positively and significantly impact income inequality.

I find the same result in responses from Order 2. Again, income inequality is positively and significantly impacted by a shock to financial size. This is confirmed in the response in Orders 3 and 4 as well. This robust finding, as mentioned previously, makes intuitive sense given that the measure of income inequality used is sensitive to financial sector fluctuations. However, the robustness of the finding still supports the hypothesis of financial sector size impacting broader income inequality.

9.2 Long-Run Restrictions

Assuming the long-run SVAR model VMA form of $y_t = Ce_t$, I impose restriction on the C matrix to test long-run identifying restrictions. Six restrictions must be imposed again to just-identify the model. The ordering is arguably less significant in testing the long-run restrictions, thus I only use the same ordering used in all previous model, or Order 1 from the previous section.

Note that in following the Blanchard-Quah long-run identification methodology, the system must be stationary. Therefore I take the first-differences of each variable in Order 1, since each was identified to be a unit root in Table 1. In order for the model to have valid inference and possess normal residuals, I include dummy variables $dum28t$, $dum80p$, $dum81p$, $dum86p$ and $dum01p$ in the model as well.

Because all variables in the model are real, it is difficult to intuit identification of the shocks. Blanchard-Quah consider the shocks to be exogenous and the system variables to be endogenous, thus one possible interpretation may be that each shock in the VMA model is an institutional shock to that respective economic sector. For example, a new income or capital gains tax policy might correspond to an e_{1t} shock and housing credit legislation could correspond to an e_{3t} shock.

As a baseline exercise, I first test that each variable is only affected in the long run by its own shocks–that is, C is a diagonal matrix. As an over-identified restriction it is strongly rejected by the LR test with a p-value of 0.0001. There must exist some long-run impacts between variables in the system.

I test the following over-identified model. Suppose shocks to the interest rate have no long-run effect on income inequality nor on household credit. Because it was observed earlier that income inequality and household credit are strongly inversely related in the CVAR model, this makes intuitive sense. At the same time, income inequality shocks have no long-run impact on any of the other variables. I assume household credit is impacted only by its own shocks, thus the growth of the financial sector could be related to other intermediary functions. However given our earlier findings about Granger causality between household credit and the interest rate, I only assume that the interest rate is not affected by income inequality or financial sector size shocks.

This embeds tests of the argument presented in Greenwood & Jovanovic (1990), that income inequality across agents "converges" as the financial sector becomes highly developed. Thus I would expect to see no long-run effect on income inequality from shocks to either financial sector size or household credit. At the same time, interest rate shocks would also not be expected to have long-run effects since agents and households would be expected to adjust their savings or consumption behavior to the new rate. The tested model looks like

$$y_t = \begin{pmatrix} c_1 & c_2 & c_4 & 0 \\ 0 & c_3 & c_5 & c_8 \\ 0 & 0 & c_6 & 0 \\ 0 & 0 & c_7 & c_9 \end{pmatrix} e_t \tag{12}$$

The estimation results are presented in the Appendix, Section P.2. The null of the over-identified system being valid is accepted with a $\chi^2(1)$ test statistic of 0.407 and p-value of 0.5233.

The corresponding impulse response functions of the firs-differences are presented in Figure 35 (Appendix, Section P.2). There are no noticeably significant long-run responses in changes of rate for any series, unlike the contemporaneous responses in levels observed above.

10 Conclusion

This paper estimated three different VAR(k) models in order to study the relationship between US income inequality and financial sector size. In the CVAR model I focussed on the statistical inference the model provides, given our normality assumption holding, and discerned long-run equilibria and short-run adjustments–i.e., the pushing and pulling forces of the system. Though there existed only one cointegrating relation, given the accepted normality of the residuals in the system its value is robust. It suggested a strong inverse relationship between income inequality (measured as the top 0.01%'s share of income, including capital gains) and household credit, and a stronger comoving relationship between the size of the financial sector and income inequality.

Further analysis using the simplified UVAR and SVAR models confirmed this general relationship. Impulse responses, for various orderings of the variables, consistently showed a significant and positive relationship between positive shocks to the size of the financial sector and income inequality.

These findings do not necessarily support the nonlinearity of the conjectured "Kuznets" curve, a hypothetical inverted-U shaped curve relating income inequality and growth. Greenwood &

Jovanovic (1990) suggest this relationship, based on initially low economic development and growth, is sustained through financial development. My data, however, span a long time-period of US economic and financial development and presents a contradictory long-run equilibrium. It may be that relative economic development is the critical variable, as the US has consistently had very high per capita income and output.

Further research will consider other annual measures that relate to income inequality, such as the output gap, and components of the financial sector, such as private versus household leverage. Additionally, the long-run relationship of net household assets is of potentially greater importance in determining macroeconomic outcomes.

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A Appendix

A US Income Inequality, Alternative Measures

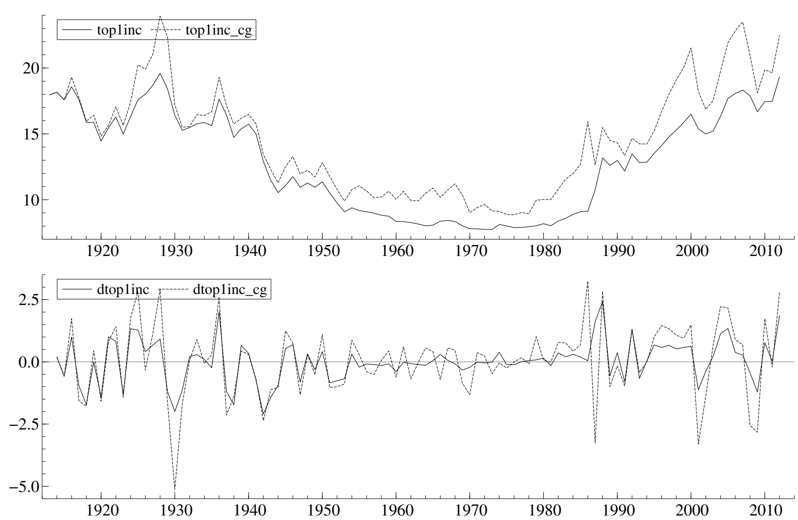


Figure 4: Top 0.1% Share of Income (incl. Capital Gains)

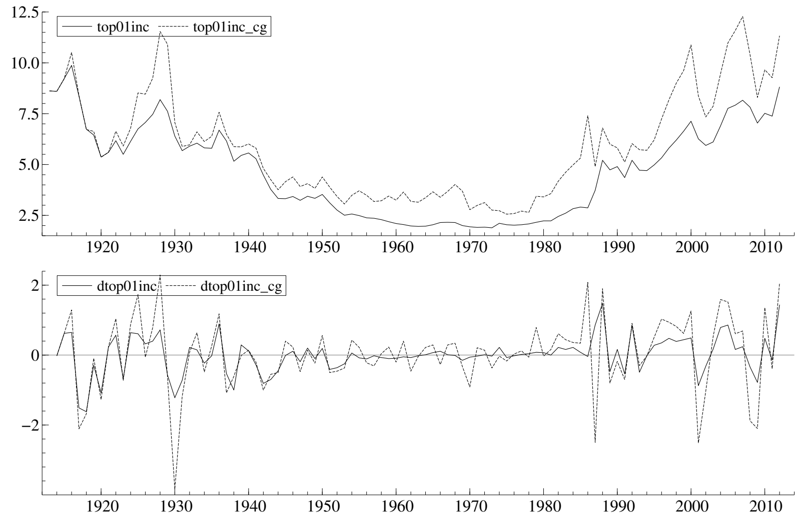


Figure 5: Top 0.01% Share of Income (incl. Capital Gains)

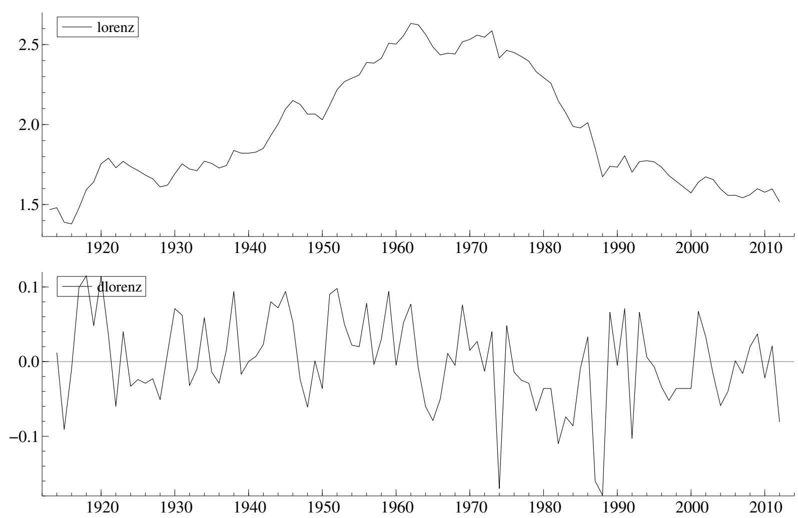


Figure 6: Pareto-Lorenz Coefficient

B Unrestricted Model Estimates

CATS Output

β'					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
Beta(1)	0.741	−1.406	0.570	0.009	−0.017
Beta(2)	−0.945	1.016	0.354	−0.162	−0.055
Beta(3)	−0.945	−0.198	0.277	−0.282	−0.002
Beta(4)	0.574	−0.407	−0.277	0.131	0.076

α				
	Alpha(1)	Alpha(2)	Alpha(3)	Alpha(4)
DTOP00	−0.125	0.118	0.064	0.027
	[−3.480]	[3.289]	[1.772]	[0.743]
DEFINS	0.028	−0.008	0.014	0.064
	[1.338]	[−0.355]	[0.646]	[3.013]
DFINFH	−0.267	−0.123	0.031	0.032
	[−5.603]	[−2.587]	[0.661]	[0.668]
DGOVBR	0.112	−0.088	0.143	−0.055
	[2.207]	[−1.730]	[2.807]	[−1.089]

Π					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
DTOP00	−0.249	0.272	−0.019	−0.035	−0.002
	[−4.249]	[4.229]	[−0.690]	[−2.761]	[−0.709]
DEFINS	0.052	−0.076	−0.000	0.006	0.005
	[1.498]	[−2.005]	[−0.024]	[0.804]	[2.342]
DFINFH	−0.093	0.231	−0.196	0.013	0.014
	[−1.193]	[2.704]	[−5.291]	[0.770]	[3.036]
DGOVBR	−0.000	−0.253	0.088	−0.032	−0.002
	[−0.004]	[−2.775]	[2.222]	[−1.804]	[−0.331]

C Specification Testing

Variable	Test	Dist.	Test stat.	p-value
top001inccg	Normality test	$\chi^2(2)$	1.4102	[0.4941]
efinshv	Normality test	$\chi^2(2)$	0.46831	[0.7912]
finfhh	Normality test	$\chi^2(2)$	0.15466	[0.9256]
govBr	Normality test	$\chi^2(2)$	4.5893	[0.1008]
	Vector Normality test	$\chi^2(2)$	8.1336	[0.4205]

Table 9: Normality Testing of Specified Model Using Reduced-form Residuals (PcGive)

	Mean	Std.Dev	Skewness	Kurtosis	Maximum	Minimum
DTOP001INCCG	-0.000	0.350	0.041	3.284	0.939	-0.972
DEFINSHV	0.000	0.206	0.034	3.052	0.513	-0.496
DFINFHH	-0.000	0.464	-0.091	2.758	0.978	-1.173
DGOVBR	0.000	0.495	0.195	3.784	1.403	-1.338

	ARCH(2)		Normality		R-Squared
DTOP001INCCG	3.616	[0.164]	1.410	[0.494]	0.605
DEFINSHV	5.151	[0.076]	0.468	[0.791]	0.438
DFINFHH	0.350	[0.840]	0.155	[0.926]	0.677
DGOVBR	10.146	[0.006]	4.589	[0.101]	0.548

Table 10: Residual Analysis of Unrestricted Specified Model (CATS)

D Residual Analysis Plots (in CATS)

Actual and fitted values of Δx_t (top left), standardized residuals (bottom left), autocorrelations (top right), and histogram of the standardized residuals that includes Kolmogorov-Smirnov and Jarque-Bera test statistics for normality(bottom right). Overlaid on the histogram is the estimated density function (dashed line) of the standardized residuals compared to the standard normal (solid line).

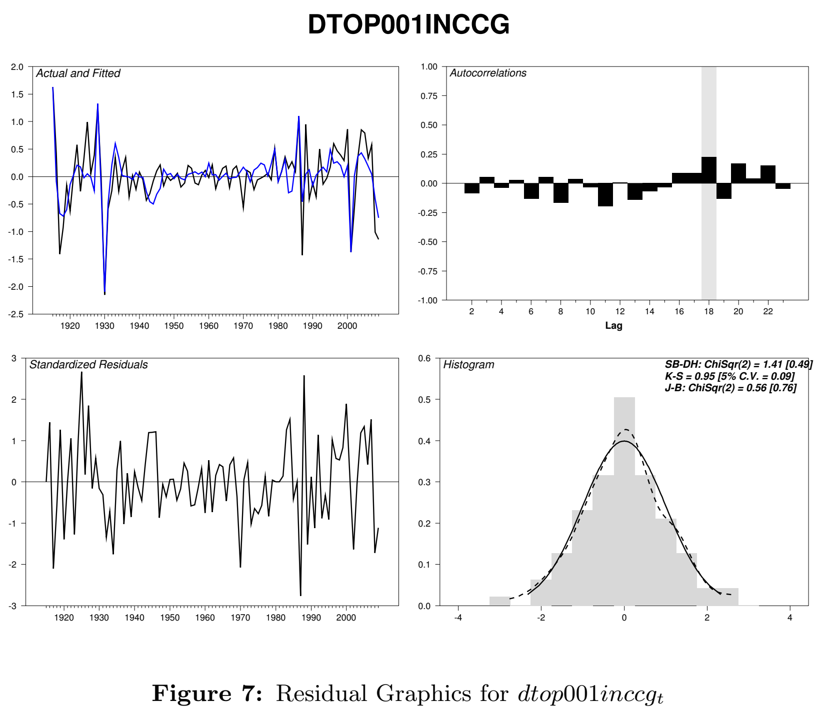


Figure 7: Residual Graphics for $dtop001inccg_t$

DEFINSHV

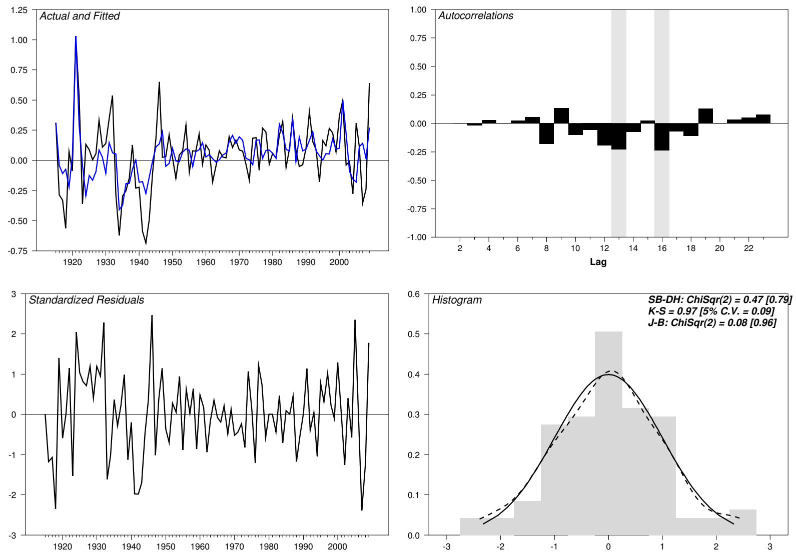


Figure 8: Residual Graphics for $definshv_t$

DFINFHH

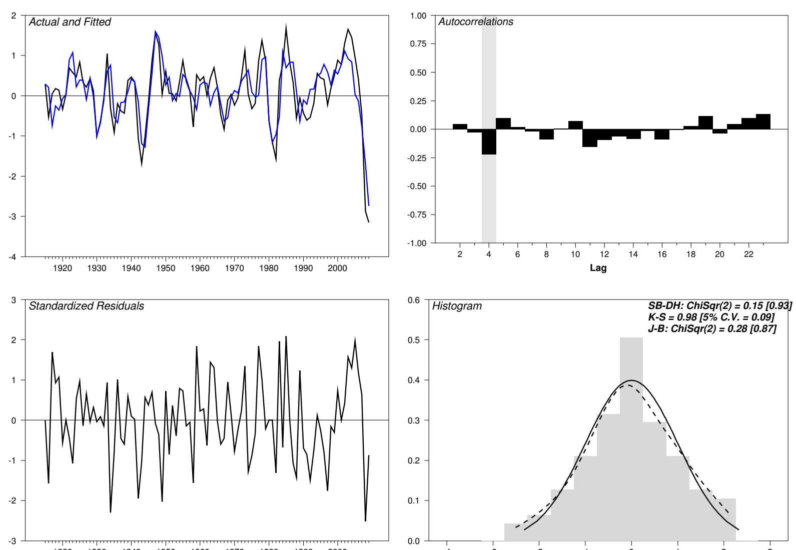


Figure 9: Residual Graphics for $dfinfhh_t$

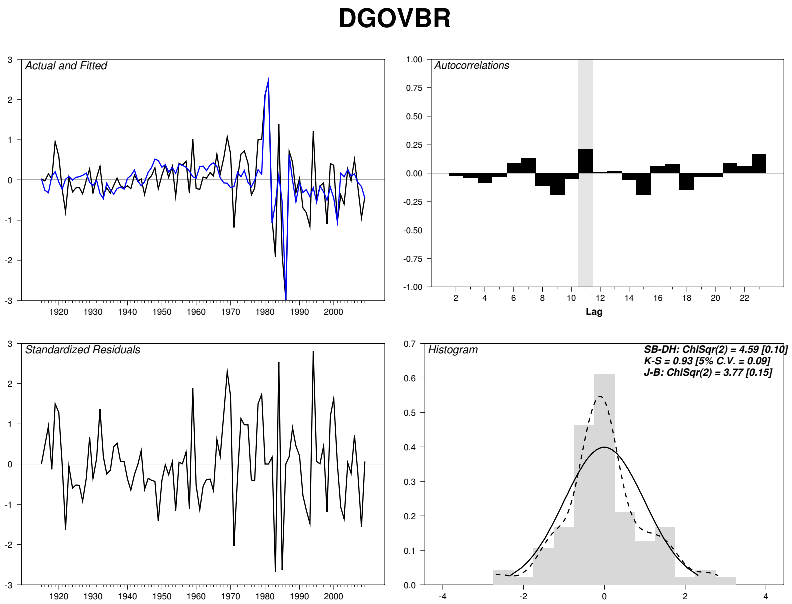


Figure 10: Residual Graphics for $dgovBr_t$

E Cointegration Rank (in CATS)

The Roots of the COMPANION MATRIX // Model: H(4)				
	Real	Imaginary	Modulus	Argument
Root1	0.999	0.000	0.999	0.000
Root2	0.925	0.000	0.925	0.000
Root3	0.671	−0.455	0.811	−0.595
Root4	0.671	0.455	0.811	0.595
Root5	0.628	−0.126	0.640	−0.198
Root6	0.628	0.126	0.640	0.198
Root7	0.194	0.000	0.194	0.000
Root8	−0.108	0.000	0.108	3.142

Table 11: Roots of Companion Matrix Estimated

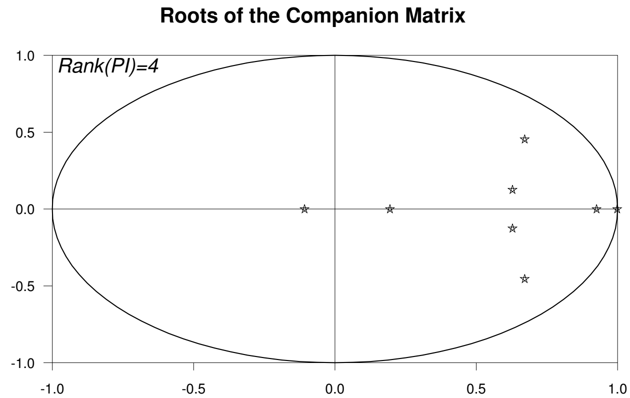


Figure 11

Rank Test Statistics:

I(1)-ANALYSIS							
p-r	r	Eig.Value	Trace	Trace*	Frac95	P-Value	P-Value*
4	0	0.336	81.894	75.298	63.659	0.001	0.003
3	1	0.210	42.960	40.313	42.770	0.048	0.088
2	2	0.112	20.615	18.368	25.731	0.200	0.327
1	3	0.094	9.360	7.175	12.448	0.163	0.336

Simulating the Rank Test Distribution
Below is reported the simulated quantiles of the asymptotic distribution of the rank test statistic.

Deterministic specification: Restricted Linear Trend (CIDRIFT)

Number of Replications (N): 2500
Length of Random Walks (T): 400

Quantiles of the Simulated Rank Test Distribution									
p-r	r	50%	75%	80%	85%	90%	95%	97.5%	99%
4	0	48.078	8.710	47.397	53.381	55.020	56.930	59.508	63.271
3	1	30.299	6.810	29.685	34.441	35.826	37.284	39.489	42.538
2	2	16.491	5.216	15.731	19.555	20.621	22.029	23.519	25.932
1	3	6.238	3.294	5.588	7.872	8.531	9.349	10.623	12.380

The I(1) analysis based on the simulated critical values:

I(1)-ANALYSIS							
p-r	r	Eig.Value	Trace	Trace*	Frac95	P-Value	P-Value*
4	0	0.336	81.894	75.298	63.271	0.001	0.003
3	1	0.210	42.960	40.313	42.538	0.043	0.080
2	2	0.112	20.615	18.368	25.932	0.201	0.326
1	3	0.094	9.360	7.175	12.380	0.160	0.328

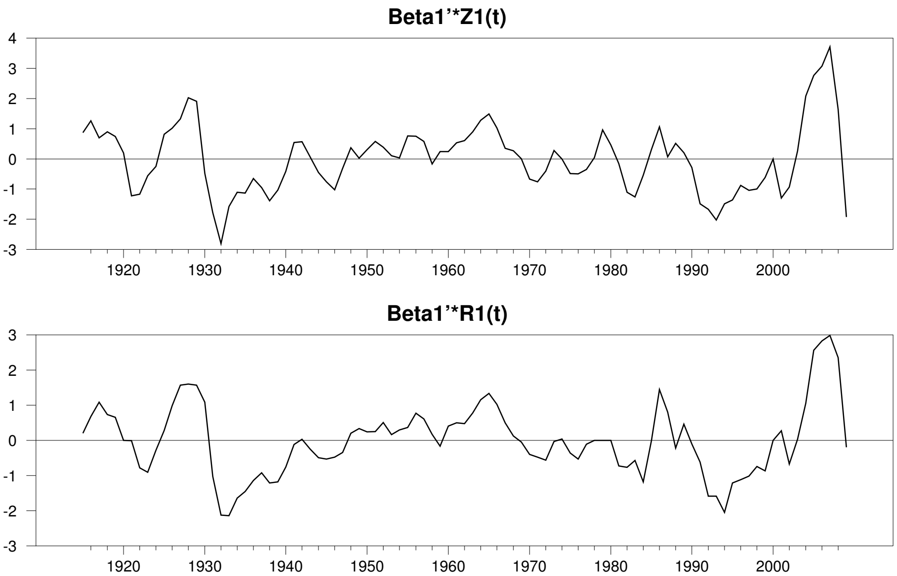


Figure 12: Plot of the first, and only, cointegrating relation when $r = 1$. The bottom plot is corrected for short-run effects.

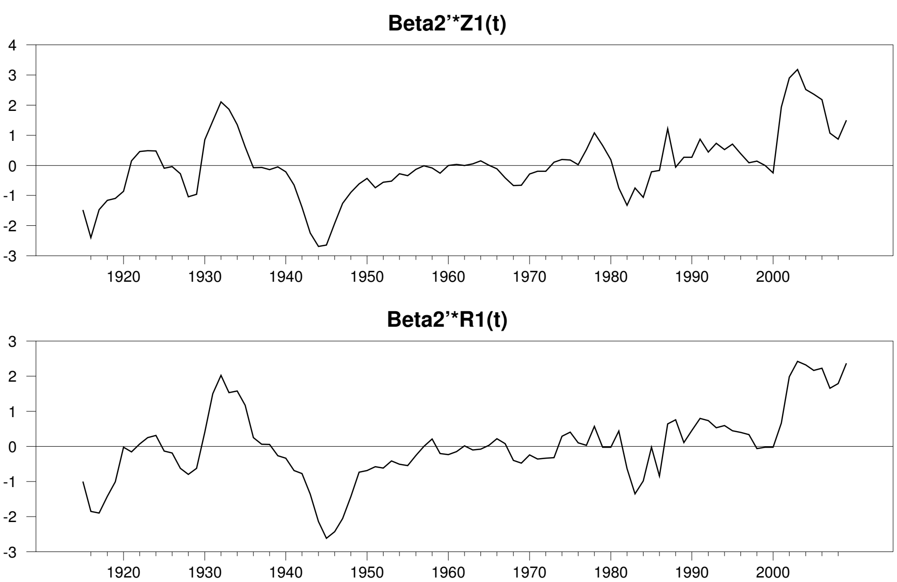


Figure 13: Plot of second cointegrating relation when $r = 2$. The bottom plot is corrected for short-run effects.

F Recursive Testing of CVAR Model

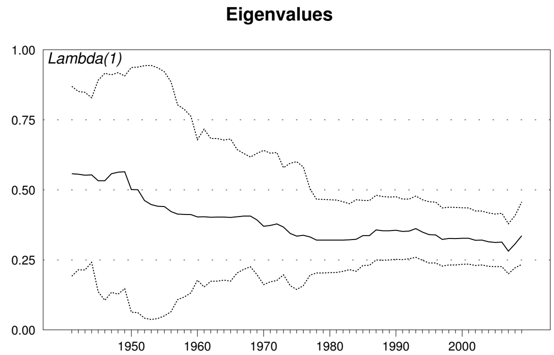


Figure 14: Forward Recursive Test of Eigenvalue, where $r = 1$

In the below plots, R_1 equals the residual from regressing $\mathbf{x_t}$ on the unrestricted variables, with a rank of Pi set to 1.

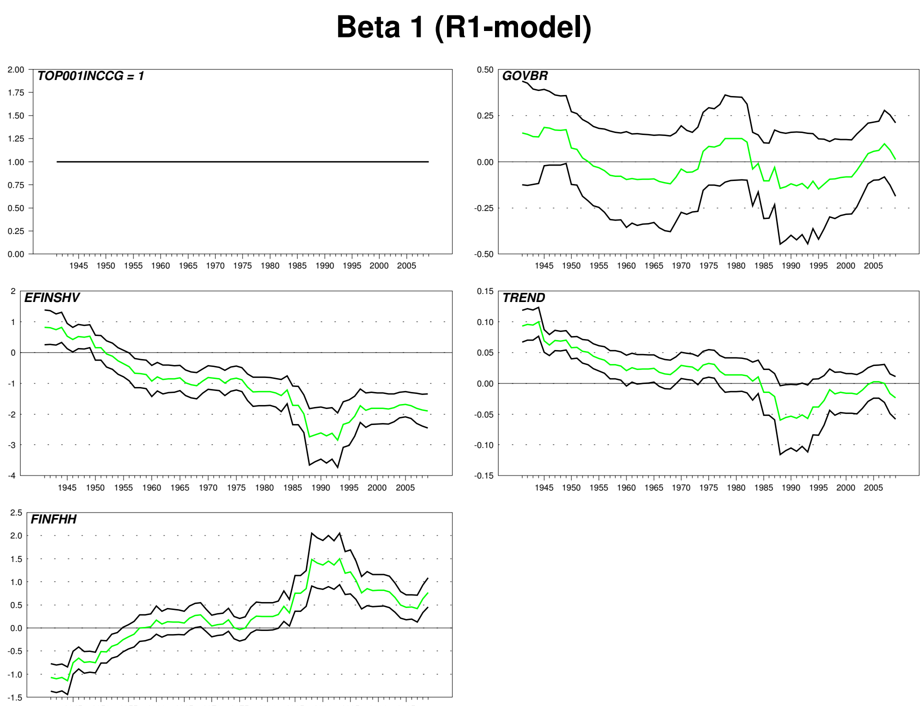


Figure 15: Forward Recursive Test of β_1^c Vector (Adjusted for SR Effects)

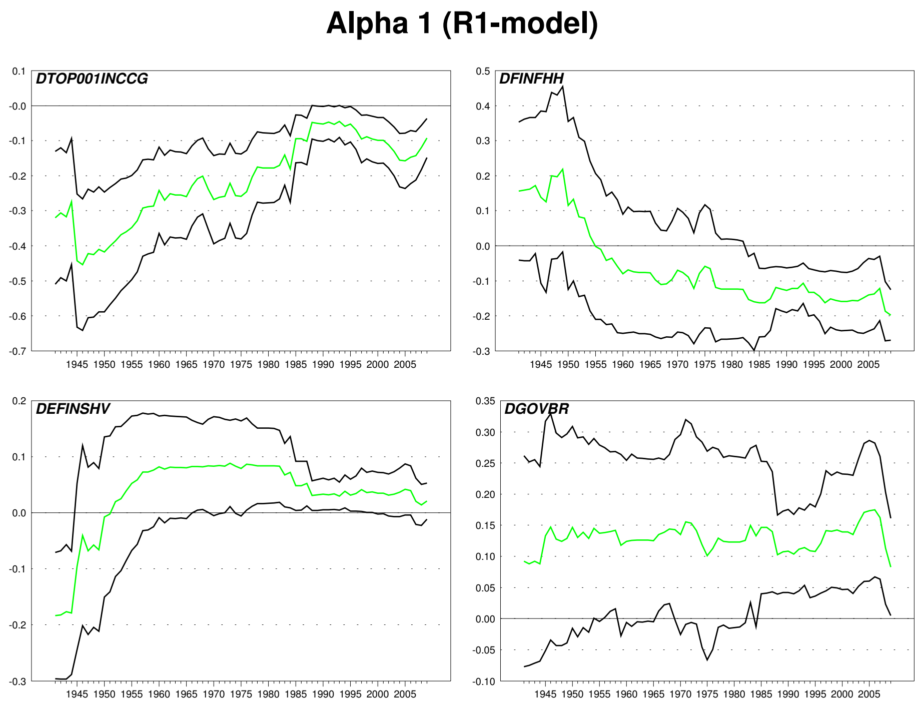


Figure 16: Forward Recursive Test of α_1 Vector (Adjusted for SR Effects)

G CVAR Model Specific Data Properties

r	DGF	5% C.V.	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	1	3.841	5.344	1.273	11.817	2.912
			[0.021]	[0.259]	[0.001]	[0.088]
2	2	5.991	12.481	1.347	21.988	4.607
			[0.002]	[0.510]	[0.000]	[0.100]
3	3	7.815	14.108	1.417	23.297	6.220
			[0.003]	[0.702]	[0.000]	[0.101]

Table 12: Test of Weak Exogeneity (LR-Test, Chi-Square(r), P-values in brackets)

r	DGF	5% CV	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	3	7.815	17.360	25.459	7.775	23.990
			[0.001]	[0.000]	[0.051]	[0.000]
2	2	5.991	3.159	12.504	0.236	9.969
			[0.206]	[0.002]	[0.889]	[0.007]
3	1	3.841	0.008	1.833	0.171	0.155
			[0.931]	[0.176]	[0.679]	[0.694]

Table 13: Test of Unit Vector in Alpha (LR-test, Chi-Square(4-r), P-values in brackets)

H Unrestricted Model Estimates, Rank $r = 1$ Imposed

THE EIGENVECTOR(s)(transposed)					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
Beta(1)	0.741	−1.406	0.570	0.009	−0.017

The matrices based on 1 cointegrating vector:

β'					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
Beta(1)	0.741	−1.406	0.570	0.009	−0.017

α	
	Alpha(1)
DTOP00	−0.125 [−3.242]
DEFINS	0.028 [1.275]
DFINFH	−0.267 [−5.393]
DGOVBR	0.112 [2.079]

Π					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
DTOP00	−0.092 [−3.242]	0.176 [3.242]	−0.071 [−3.242]	−0.001 [−3.242]	0.002 [3.242]
DEFINS	0.021 [1.275]	−0.040 [−1.275]	0.016 [1.275]	0.000 [1.275]	−0.000 [−1.275]
DFINFH	−0.198 [−5.393]	0.375 [5.393]	−0.152 [−5.393]	−0.002 [−5.393]	0.005 [5.393]
DGOVBR	0.083 [2.079]	−0.158 [−2.079]	0.064 [2.079]	0.001 [2.079]	−0.002 [−2.079]

I Restricted Model Estimates, Rank $r = 1$ Imposed

Long-Run Restrictions imposed on $\beta^c_{14} = 0$ and $\beta^c_{15} = 0$ of the long-run equilibrium cointegration vector, $\beta^{c'}_1$.

TEST OF RESTRICTED MODEL: CHISQR(2) = 0.773 [0.679]
BARTLETT CORRECTION: CHISQR(2) = 0.573 [0.751] (Correction Factor: 1.348)

*** NOTE: The correction factor is based on the 'Basic Model'.

Re-Normalization of the Eigenvectors:

THE EIGENVECTOR(s)(transposed)					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
Beta(1)	−0.905	1.516	−0.473	0.000	0.000

The matrices based on 1 cointegrating vector:

β'					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
Beta(1)	1.000 [.NA]	−1.675 [−7.433]	0.522 [5.915]	0.000 [.NA]	0.000 [.NA]

α	
	Alpha(1)
DTOP00	−0.120 [−3.473]
DEFINS	0.031 [1.560]
DFINFH	−0.223 [−4.868]
DGOVBR	0.107 [2.205]

Π					
	TOP001INCCG	EFINSHV	FINFHH	GOVBR	TREND
DTOP00	−0.092 [−3.473]	0.176 [3.473]	−0.071 [−3.473]	0.000 [.NA]	0.000 [.NA]
DEFINS	0.031 [1.560]	−0.052 [−1.560]	0.016 [1.560]	0.000 [.NA]	0.000 [.NA]
DFINFH	−0.223 [−4.868]	0.373 [4.868]	−0.116 [−4.868]	0.000 [.NA]	0.000 [.NA]
DGOVBR	0.107 [2.205]	−0.180 [−2.205]	0.056 [2.205]	0.000 [.NA]	0.000 [.NA]

J The MA-Representation and Decomposition of the Trend, Restricted Model

The Coefficients of the Common Stochastic Trends:

$\alpha'_{\perp}$				
	TOP001INCCG	EFINSHV	FINFHH	GOVBR
CT(1)	0.182	−0.047	0.339	0.922
CT(2)	0.848	−0.211	−0.486	0.000
CT(3)	0.244	0.970	0.005	0.000

Normalized:

$\alpha'_{\perp}$				
	TOP001INCCG	EFINSHV	FINFHH	GOVBR
CT(1)	0.000 [NA]	0.000 [NA]	0.481 [1.971]	1.000 [NA]
CT(2)	1.000 [NA]	0.000 [NA]	−0.539 [−3.020]	0.000 [NA]
CT(3)	0.000 [NA]	1.000 [NA]	0.140 [1.425]	0.000 [NA]

The Loadings to the Common Trends, $\tilde{\beta}_{\perp}$:			
	CT1	CT2	CT3
TOP001	0.166 [3.126]	0.752 [7.429]	0.849 [3.761]
EFINSH	0.072 [1.154]	0.158 [1.735]	1.344 [6.634]
FINFHH	−0.086 [−0.765]	−0.934 [−4.349]	2.685 [5.608]
GOVBR	0.819 [10.581]	−0.149 [−1.011]	0.487 [1.478]

The Long-Run Impact Matrix, C				
	TOP001INCCG	EFINSHV	FINFHH	GOVBR
TOP001	0.752 [7.429]	0.849 [3.761]	−0.206 [−1.506]	0.166 [3.126]
EFINSH	0.158 [1.735]	1.344 [6.634]	0.138 [1.123]	0.072 [1.514]
FINFHH	−0.934 [−4.349]	2.685 [5.608]	0.838 [2.883]	−0.086 [−0.765]
GOVBR	−0.149 [−1.011]	0.479 [1.478]	0.543 [2.716]	0.819 [10.581]

The Linear Trends in the Levels, $C\mu$			
TOP001INCCG	EFINSHV	FINFHH	GOVBR
−0.0067	0.021	0.081	−0.019

Residual S.E. and Cross-Correlations				
	TOP001INCCG	EFINSHV	FINFHH	GOVBR
	0.361	0.324	0.766	0.526
TOP001INCCG	1.000	NA	NA	NA
EFINSHV	0.676	1.000	NA	NA
FINFHH	0.015	0.747	1.000	NA
GOVBR	0.094	0.361	0.405	1.000

K Structural MA Form of CVAR Model

K.1 Estimation of Restricted Structural MA Form

PARAMETERS OF THE STRUCTURAL MA-MODEL:

$$X_t = \tilde{C}\Sigma U_i + \tilde{C}^*(L)U_t + Deterministics$$

where U(t) = [Trans(1); Perm(1),..., Perm(3)]

*** Convergence of C*-polynomial in 31 steps.

Structural Long-Run Impact Matrix, $\tilde{C}$ (Normalized)				
	Trans(1)	Perm(1)	Perm(2)	Perm(3)
TOP001	0.000	0.064	0.504	-0.522
EFINSH	0.000	0.222	0.613	-0.000
FINFHH	0.000	0.589	1.000	1.000
GOVBR	0.000	1.000	-0.000	0.000

100*Contemporaneous impact, $\tilde{C}^{*}(0)$				
	Trans(1)	Perm(1)	Perm(2)	Perm(3)
TOP001	-18.879	-1.546	15.700	27.977
EFINSH	4.912	3.685	20.546	-2.385
FINFHH	-35.042	27.944	8.963	-18.554
GOVBR	16.866	43.305	-15.290	18.813

100*Impact After 31 Periods:				
	Trans(1)	Perm(1)	Perm(2)	Perm(3)
TOP001	-0.014	3.383	24.850	25.973
EFINSH	-0.001	11.699	30.234	-0.008
FINFHH	-0.035	31.020	49.297	-49.672
GOVBR	0.010	52.640	-0.006	0.004

RE-NORMALIZATION OF B:

Rotation Matrix, B: $[U_t = \mathrm{B}\varepsilon_t]$				
	EPS(1)	EPS(2)	EPS(3)	EPS(4)
Trans(1)	-1.298	2.189	-1.495	0.732
Perm(1)	-0.283	0.924	1.031	1.555
Perm(2)	0.631	4.089	0.058	-0.363
Perm(3)	2.329	-0.767	-0.985	0.784

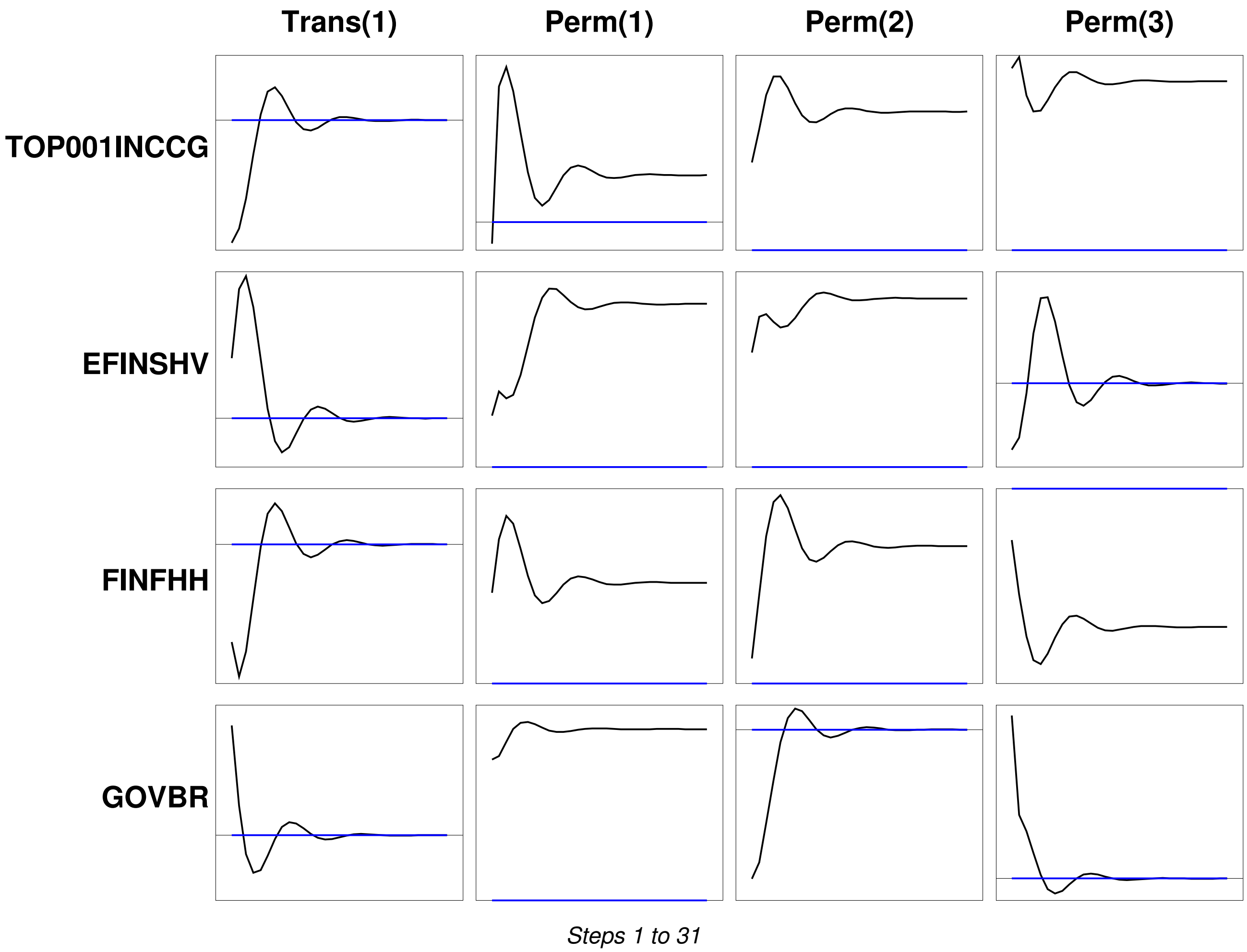
Rotation Matrix, B (Normalized)				
	EPS(1)	EPS(2)	EPS(3)	EPS(4)
Trans(1)	-0.593	1.000	-0.683	0.335
Perm(1)	-0.182	0.594	0.663	1.000
Perm(2)	0.154	1.000	0.014	-0.089
Perm(3)	1.000	-0.329	-0.423	0.337

RE-NORMALIZATION OF INVERSE(B):

Inverse Rotation Matrix, B^{-1}: $[\varepsilon_t = B^{-1}U_t]$				
	Trans(1)	Perm(1)	Perm(2)	Perm(3)
EPS(1)	-0.189	-0.015	0.157	0.280
EPS(2)	0.049	0.037	0.205	-0.024
EPS(3)	-0.350	0.279	0.090	-0.186
EPS(4)	0.169	0.433	-0.153	0.188

Inverse Rotation Matrix, B^{-1} (Normalized)				
	Trans(1)	Perm(1)	Perm(2)	Perm(3)
EPS(1)	-0.675	-0.055	0.561	1.000
EPS(2)	0.239	0.179	1.000	-0.116
EPS(3)	1.000	-0.797	-0.256	0.529
EPS(4)	0.389	1.000	-0.353	0.434

K.2 Impulse Response Functions, Structural MA Form



L Variance Decomposition of UVAR Model

Variance Decomposition of TOP001INCCG:

Period	S.E.	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	0.384039	100.0000	0.000000	0.000000	0.000000
2	0.561267	94.36298	2.763774	0.181673	2.691576
3	0.669000	86.65151	10.43730	0.355713	2.555476
4	0.747756	77.91350	19.61564	0.284763	2.186092
5	0.809039	70.38259	27.26646	0.459764	1.891184
6	0.856804	64.83021	32.58324	0.898472	1.688075
7	0.894055	61.02314	36.16862	1.257423	1.550819
8	0.924622	58.34837	38.84817	1.347956	1.455498
9	0.952633	56.15393	41.18232	1.277148	1.386608
10	0.981327	53.94624	43.46150	1.256781	1.335481

Variance Decomposition of EFINSHV:

Period	S.E.	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	0.231018	2.695170	97.30483	0.000000	0.000000
2	0.384596	1.455656	97.56613	0.604748	0.373463
3	0.491219	1.138605	97.27795	0.986257	0.597186
4	0.563748	1.319113	97.01934	0.830384	0.831167
5	0.620644	1.907912	96.13642	0.926762	1.028907
6	0.677045	2.614863	93.89171	2.359044	1.134381
7	0.740075	3.044380	90.60233	5.209866	1.143424
8	0.809296	3.056384	87.23891	8.606881	1.097826
9	0.880500	2.790807	84.44242	11.72293	1.043840
10	0.949363	2.447625	82.27785	14.26396	1.010565

Variance Decomposition of FINFHH:

Period	S.E.	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	0.526510	3.723559	1.833964	94.44248	0.000000
2	1.029007	2.439370	10.14885	87.10148	0.310303
3	1.474071	1.279278	19.86278	78.52281	0.335127
4	1.831299	1.028274	28.37684	70.29957	0.295310
5	2.096858	1.620476	34.39883	63.74461	0.236078
6	2.284198	2.608703	37.87687	59.30917	0.205255
7	2.415156	3.577159	39.41357	56.76316	0.246105
8	2.512685	4.313106	39.69640	55.60920	0.381291
9	2.595399	4.792249	39.22385	55.37600	0.607899
10	2.674646	5.088056	38.30993	55.69554	0.906480

Variance Decomposition of GOVBR:

Period	S.E.	TOP001INCCG	EFINSHV	FINFHH	GOVBR
1	0.543157	0.244724	0.864378	0.029677	98.86122
2	0.700267	0.505116	0.871053	5.477260	93.14657
3	0.843152	0.442446	0.819990	13.10407	85.63350
4	0.977949	0.446656	0.685474	20.62024	78.24763
5	1.102442	0.638981	0.561878	26.59778	72.20137
6	1.214879	1.110009	0.486873	30.70238	67.70074
7	1.316100	1.861932	0.499067	33.19118	64.44782
8	1.408899	2.805842	0.699138	34.47898	62.01604
9	1.496628	3.815890	1.218403	34.93344	60.03227
10	1.582059	4.786506	2.147435	34.82213	58.24393

M Granger Causality in UVAR Model

Pairwise Granger Causality Tests Date: 12/13/13 Time: 20:38 Sample: 1913 2012 Lags: 2 Null Hypothesis:	Obs	F-Statistic	Prob.
EFINSHV does not Granger Cause TOP001INCCG	95	3.97754	0.0221*
TOP001INCCG does not Granger Cause EFINSHV		1.16630	0.3162
FINFHH does not Granger Cause TOP001INCCG	97	2.12787	0.1249
TOP001INCCG does not Granger Cause FINFHH		0.77291	0.4646
GOVBR does not Granger Cause TOP001INCCG	98	0.24670	0.7819
TOP001INCCG does not Granger Cause GOVBR		2.05209	0.1342
FINFHH does not Granger Cause EFINSHV	95	4.06258	0.0205*
EFINSHV does not Granger Cause FINFHH		11.7865	3.E-05**
GOVBR does not Granger Cause EFINSHV	95	2.05679	0.1338
EFINSHV does not Granger Cause GOVBR		0.66190	0.5184
GOVBR does not Granger Cause FINFHH	97	4.85010	0.0099**
FINFHH does not Granger Cause GOVBR		0.53966	0.5848

** = significance at 1%, * = significance at 5%

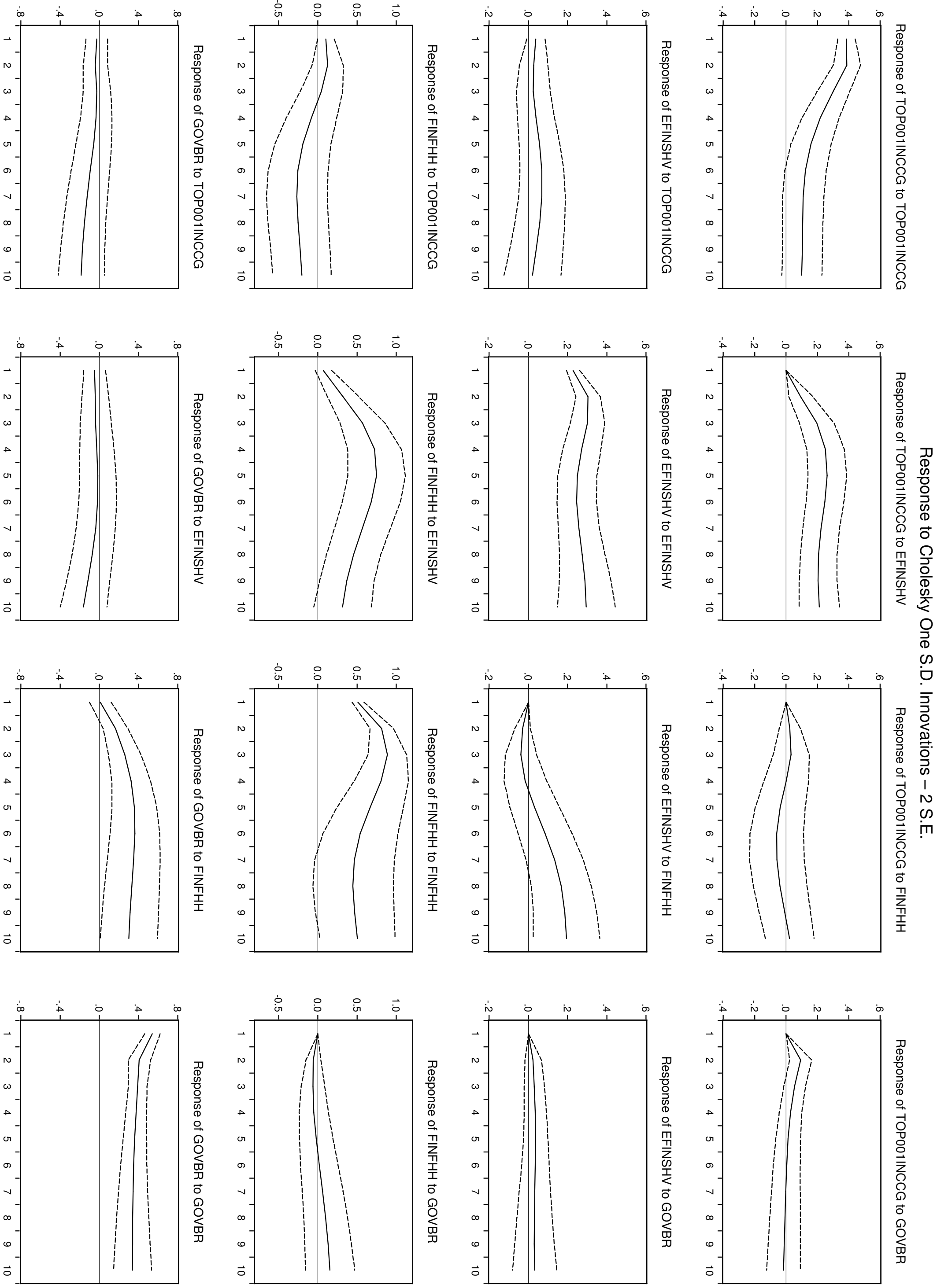
Table 14: Pairwise Granger Causality Tests (EViews)

VAR Granger Causality/Block Exogeneity Wald Tests Date: 12/13/13 Time: 20:35 Sample: 1913 2012 Included observations: 95 Dependent variable: TOP001INCCG	Chi-sq	df	Prob.
EFINSHV	17.79533	2	0.0001**
FINFHH	3.549103	2	0.1696
GOVBR	10.62266	2	0.0049**
All	34.10589	6	0.0000**
Dependent variable: EFINSHV			
TOP001INCCG	1.166688	2	0.5580
FINFHH	9.091346	2	0.0106*
GOVBR	1.561927	2	0.4580
All	15.81148	6	0.0148*
Dependent variable: FINFHH			
TOP001INCCG	9.659129	2	0.0080**
EFINSHV	19.94283	2	0.0000**
GOVBR	2.037645	2	0.3610
All	40.51986	6	0.0000**
Dependent variable: GOVBR			
TOP001INCCG	1.424477	2	0.4905
EFINSHV	6.779475	2	0.0337*
FINFHH	14.35062	2	0.0008**
All	18.14307	6	0.0059**

** = significance at 1%, * = significance at 5%

Table 15: VAR Granger Causality Tests (EViews)

N Impulse Response Functions in UVAR Model



O SVAR Model

O.1 Short-Run Impulse Response Functions from Cholesky Identification

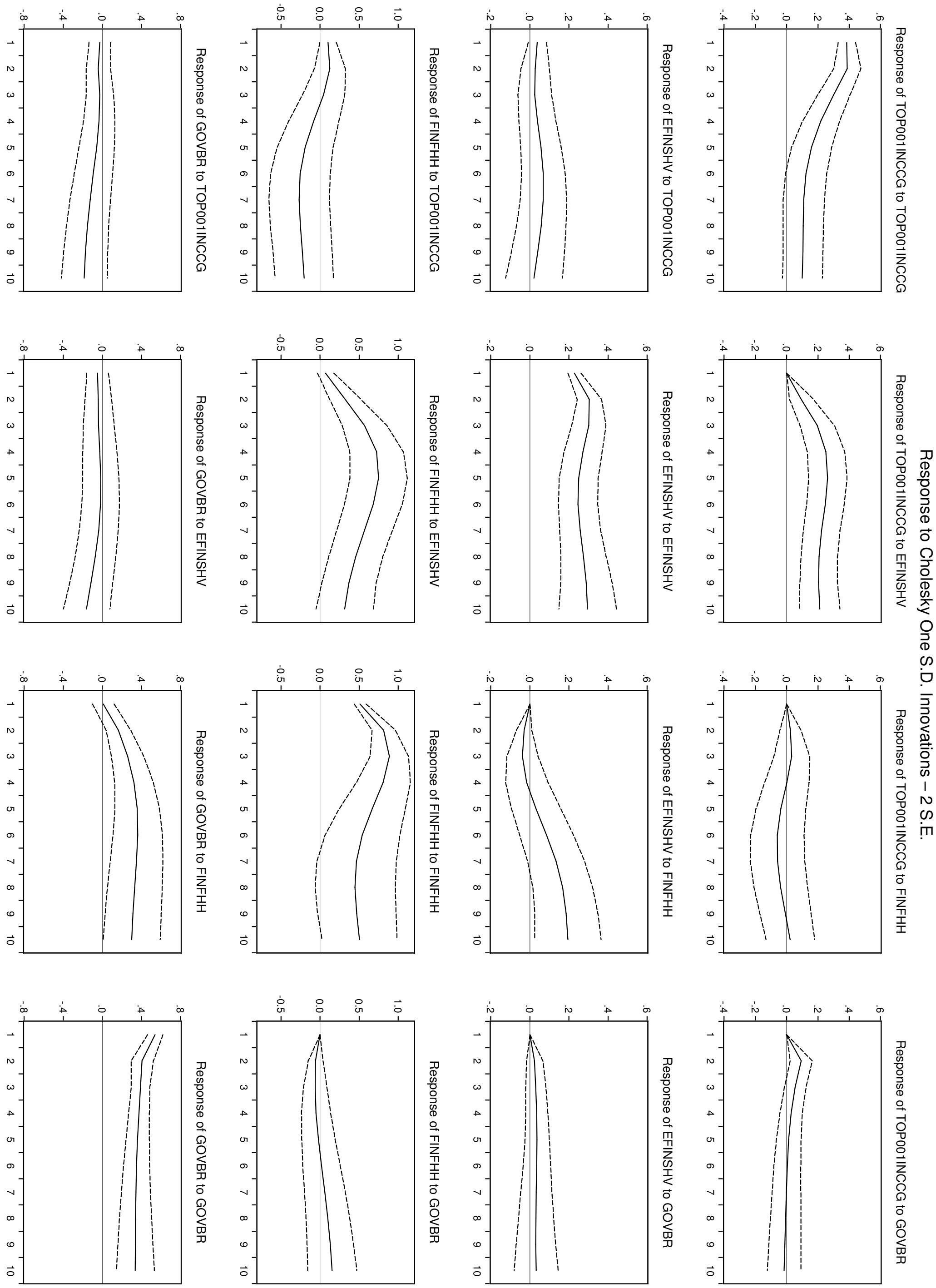


Figure 17: Order 1 of Variables $[top001incg, efinshv, finfhh, govBr]$'

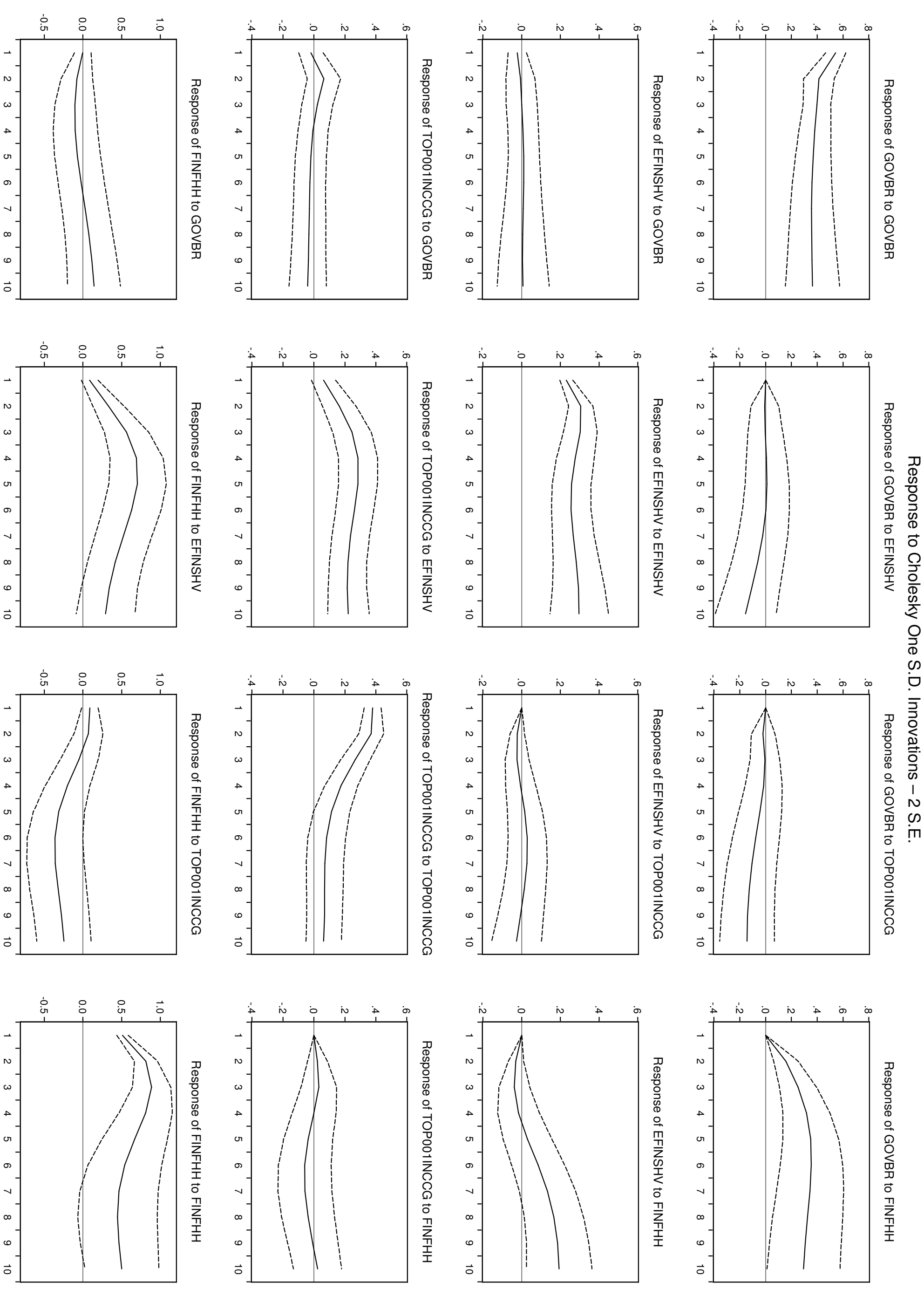


Figure 18: Order 2 of Variables $[govBr, efinshv, top001incg, finfhh]$'

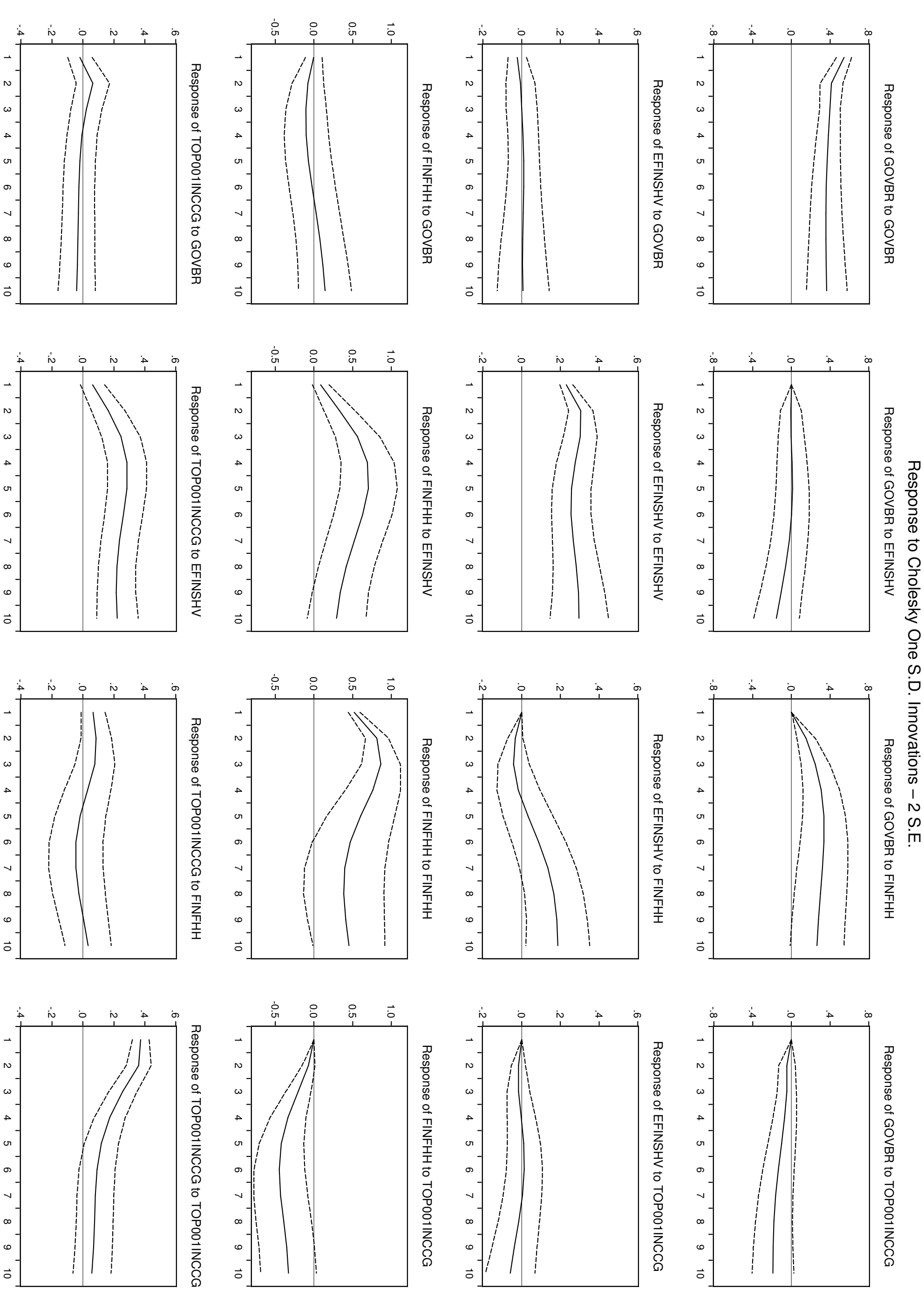


Figure 19: Order 3 of Variables [$govBr$,$efinshv$,$finfhh$,$top001incg$]'

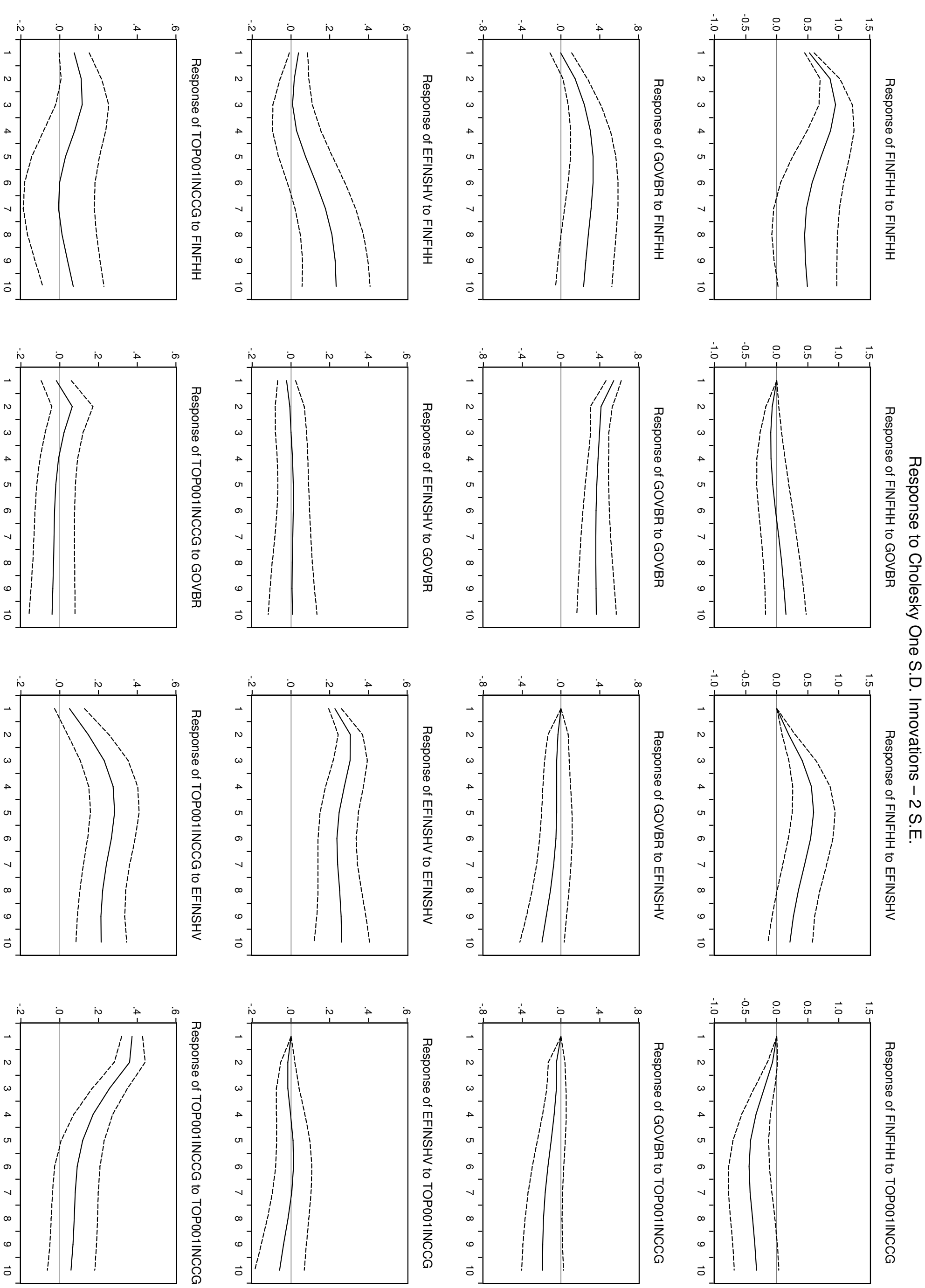


Figure 20: Order 4 of Variables [$finfhh$,$govBr$,$efinshv$,$top001incg$]'

O.2 Long-Run Estimation

Structural VAR Estimates:

Sample (adjusted): 1916 2009
Included observations: 94 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 9 iterations
Structural VAR is over-identified (1 degrees of freedom)

Model: Ae = Bu where E[uu']=I
Restriction Type: long-run text form
Long-run response pattern

C(1)	C(2)	C(4)	0
0	C(3)	C(5)	C(8)
0	0	C(6)	0
0	0	C(7)	C(9)

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.428548	0.031255	13.71131	0.0000
C(2)	0.023154	0.044234	0.523453	0.6007
C(3)	0.337218	0.024594	13.71131	0.0000
C(4)	0.189243	0.046368	4.081360	0.0000
C(5)	0.086441	0.035706	2.420916	0.0155
C(6)	1.068773	0.077948	13.71131	0.0000
C(7)	0.079872	0.047181	1.692898	0.0905
C(8)	-0.048890	0.034913	-1.400336	0.1614
C(9)	0.453935	0.033107	13.71131	0.0000
Log likelihood	-212.2315			
LR test for over-identification:				
Chi-square(1)	0.407429		Probability	0.5233

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000
0.000000	1.000000	0.000000	0.000000
0.000000	0.000000	1.000000	0.000000
0.000000	0.000000	0.000000	1.000000

Estimated B matrix:

0.416561	-0.035830	0.019131	-0.053349
0.032961	0.210631	0.133632	-0.057138
0.115418	-0.231004	0.490542	0.096565
0.022604	0.155558	-0.096510	0.532915

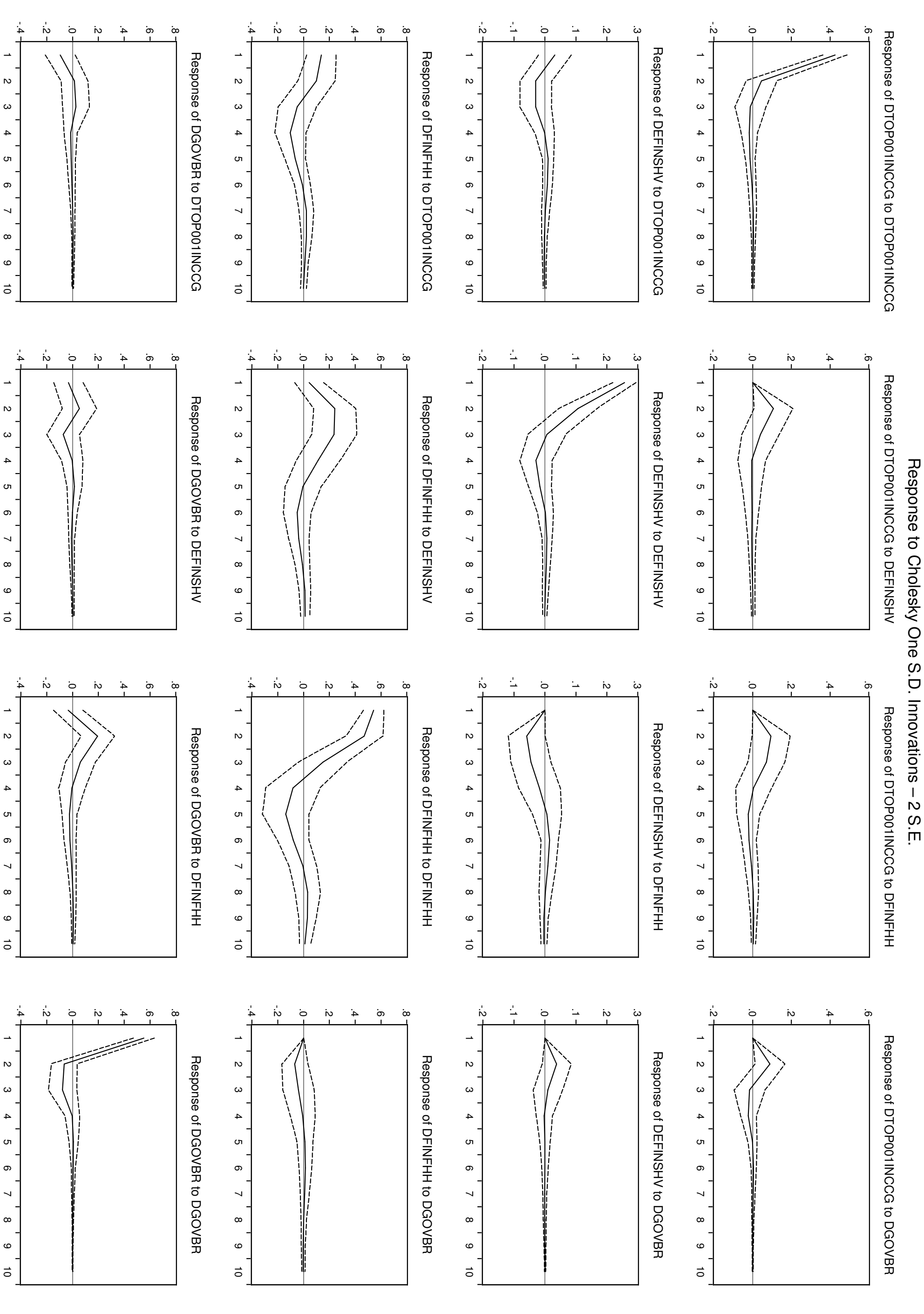


Figure 21: IRF's of LR Identification of SVAR