Empirical Identification of the Vector Autoregression: The Causes and Effects of U.S. M2

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25 July 2007

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This paper was written to present at the Conference in Honour of David F. Hendry at Oxford University, 23-27 August 2007.

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A commonplace in economics is that theory and empirics stand in a position of mutual support.[1] But there can be little doubt that for some time theory has had the upper hand. We see this in the widespread view that it is only through *a priori* theory that a system of equations can be identified, and we see it in the equally widespread view that data-mining – that is, using empirical data to shape the formulation of an econometric model – is, in all of it forms, an unequivocally bad thing. We are left with the odd view that theory proposes and data disposes. On this principle, empirical evidence is, at best, destructive, but cannot be constructive. In reality we find it hard to live up to such fine principles, but the economics profession naturally tries its best to hide (or disguise) its apostacy.

David Hendry belongs to the minority camp that embraces the notion that empirical investigation plays a *constructive* role in developing our understanding of the economy. In his inaugural address at the London School of Economics, "Econometrics: Alchemy or Science?" (1980), Hendry cogently made the case for constructive econometrics – a chemistry, not an alchemy. Hendry and the so-called LSE school (Gilbert 1986, Mizon 1995) recognize that, for many important economic problems, economic theory is too weak – and absent learning more about the facts on the ground – always will be too weak to fulfill the dominant role that the reigning ideology of economics assigns it. If one wants to know the truth about the economy, one often has to grub through the data with economic theory providing – at most – broad guidance and not detailed specifications. In his vital work on encompassing and general-to-specific specification search, culminating in his work on automatic model selection (particularly, in the *PCGets* software – see Hendry and Krolzig 1999, 2001; Krolzig and Hendry 2001), Hendry grasps the nettle. Rather than hiding constructive econometrics to suit the prejudices of the profession, he asks sensibly, how should it be done well.

We have long taken Hendry's side of the debate. And indeed, we have contributed something to automatic model selection in the spirit of the LSE school

[1] Kant is frequently quoted in support without a specific reference as: "Theory without empirics is empty. Empirics without theory is blind." or "Experience without theory is blind, but theory without experience is mere intellectual play." Both seem to be overly free translations of "*Gedanken ohne Inhalt sind leer, Anschauungen ohne Begriffe sind blind*" ("Thoughts without contents are empty; observations without concepts are blind" – Hoover translation); Kant (1787, part 2, section 1).

(Hoover and Perez 1999, 2004). We have also long been interested in what, at first, might seem an orthogonal concern: causality in economics (Perez 1998; Hoover 2001; Demiralp and Hoover 2003).[2] Recent developments in the graph-theoretic approach to causal modeling, however, suggest that there is a complementarity with Hendry's general-to-specific approach that has yet to be fully exploited (Spirites, Glymour, and Scheines 2000; Pearl 2000). In particular, Krolzig (2003) demonstrate that PCGets is effective at recovering the dynamic structure of a system of equations (a structural vector autoregression or SVAR) provided that one starts with a diagonal covariance matrix – in other words, provided that one knows the contemporaneous causal order of the SVAR. Graph-theoretic causal-search algorithms can aid in the discovery of that causal order, so that, together with PCGets, we have some hope of identifying the structure of the SVAR empirically (Swanson and Granger 1997; Demiralp and Hoover 2003, Hoover 2005).

In this paper we provide a concrete illustration of the complementary use of graph-theoretic causal modeling and automated general-to-specific specification search. Our problem is to identify the factors determining the U.S. M2 monetary aggregate and its role in the transmission of monetary policy – a problem for which economic theory provides only the broadest guidance.

1. Understanding M2

M2 consists of liquid deposits, small time deposits, retail money funds and currency in circulation. Even though, owing to the widespread use of alternative financial market instruments, the relationship between monetary aggregates and income growth has loosened over the last decade, the Federal Reserve still regards the pattern of M2 growth as providing information about the conditions of aggregate demand. M2 growth is monitored by the Monetary and Reserve Analysis Section of the Division of Monetary Affairs of the Board of Governors of the Federal Reserve System.[3] The section implicitly assumes a relatively rich causal structure in explaining the process of M2 growth, there are no formal studies (inside or outside the Federal Reserve) that analyze M2 growth analytically. The Federal Reserve's econometric models do forecast M2 growth, but

[2] And on which Hendry might be seen as somewhat skeptical – see Hendry *et al.* (1990), p. 184.
[3] This paper was conceived while Demiralp was employed as a staff economist in the Monetary and Reserve Analysis Section.

these models are mostly driven by the quantity theory of money, and omit many of the implicit structural considerations that the Section regards as important.

Before each meeting of the Federal Open Market Committee (FOMC), the Section prepares a contribution to the briefing document, known as the "Bluebook," in which it analyzes the growth of M2 growth in relation to a number of factors that have not yet been investigated structurally. The economic theory used is fairly broad brush. According to the quantity theory of money, the growth rate of money should equal the growth rate of nominal income, adjusting for the trend in velocity. The Section's analysis, therefore, starts by anchoring the underlying growth rate of M2 to the growth rate of GDP, and then considers "special factors" that may cause deviations of M2 growth rate from that of GDP. These special factors comprise:

i) Interest rate effects: changes in the Federal funds rate target lead to subsequent changes in the opportunity cost of holding M2 type of assets.

ii) Equity market effects: high volatility and downwards revisions to the expectations of earnings on equities earnings *ceterius paribus* boost M2 as investors substitute away from the stock market and into safe and liquid M2-type assets.

iii) Other special factors including: activity in *mortgage-backed securities*, as mortgage servicers temporarily accumulate the proceeds of pre-paid mortgages in the liquid-deposits component of M2; *tax effects*, which influence the money-market-deposit-account (MMDA) component of liquid deposits as people pay their taxes out of their savings accounts; and *currency shipments abroad*.

To illustrate, Table 1 shows the growth rates of the components of M2 as of December 2004. Comparing the second and the seventh columns shows that in the second quarter of 2004 M2 growth exceeded that of GDP growth (row 1), whereas in the third quarter it fell behind (row 2). The accelerated pace in the second quarter was attributed to: (i) mortgage refinancing activity in April (which was boosted by a decline in mortgage interest rates), and (ii) inflows from equity and bond funds as well as increased deposits of tax refunds in May. Meanwhile the slowdown in the third quarter was mostly explained by the rising opportunity cost in the face of a series of steps to tighten monetary policy. In each case, largest component of M2, liquid deposits, accounts for most of the overall growth rate (see Table 2).

Liquid Deposits, which constitute about 65 percent of M2, comprise *demand deposit accounts* (DDAs), *other certificates of deposits* (OCDs), and *savings deposits* (including MMDAs). DDAs and OCDs are the most liquid of the components of liquid deposits, and appear to respond to changes in the opportunity cost of holding M2 and similar assets. In addition to this opportunity-cost channel, running from changes in the Federal funds rate to the opportunity cost of M2 to liquid deposits, a decline in the Federal-funds-rate target may also lead to a decline in mortgage rates, a consequent rise in the mortgage refinancing, and a rise in liquid deposits to meet the temporary need of mortgage servicers to park funds for several weeks until the mortgage-backed securities are redeemed. Other transitory changes in the holdings of liquid deposits may be related to tax payments, influencing especially DDAs and OCDs. The MMDA component of liquid deposits is a close substitute for stock mutual funds and may, therefore, display sensitivity to the performance of the stock market. Events, such as domestic or international political crises, also boost the demand for safe and liquid M2 components. On the other hand, steepening of the yield curve, because of an increase in long-term yields or a looser monetary policy, may reduce the growth of liquid deposits as investors substitute into longer-term assets.

After a brief detour to set out the strategy of empirical investigation, we will in sections 3 through 6 investigate to what degree the data support qualitatively and quantitatively the Monetary and Reserve Analysis Section's informal understanding of the role of M2 in the transmission of monetary policy.

2. Empirical Identification

Our approach will be to specify a structural vector autoregression as far as possible using the tools of graph-theoretic causal-search algorithms and Hendry and Krolzig's (2001) *PcGets* software. *PcGets* is sufficiently well-known that we need not spend time on describing the principles of its operation. Although the same is not true of the graph-theoretic causal-search algorithms, we nonetheless will give only an informal sketch and refer the reader to the fuller descriptions available elsewhere.

The SVAR can be written as:

$$\mathbf{A}_0\mathbf{Y}_t = \mathbf{A}(L)\mathbf{Y}_{t-1} + \mathbf{E}_t\,, \tag{1}$$

where $\mathbf{Y}_t$ is an $n \times 1$ vector of contemporaneous variables, $\mathbf{A}_0$ is an $n \times n$ matrix with ones on the main diagonal and possibly non-zero off-diagonal elements; $\mathbf{A}(L)$ is a polynomial in the lag operator, L; and $\mathbf{E}_t$ is an $n \times 1$ vector of error terms with $\mathbf{E} = [\mathbf{E}_t]$, $t = 1, 2, \ldots,$ T and the covariance matrix $\boldsymbol{\Sigma} = \mathrm{E}(\mathbf{EE}')$ diagonal. The individual error terms (shocks) can be assigned unequivocally to particular equations because $\boldsymbol{\Sigma}$ is diagonal. The matrix $\mathbf{A}_0$ defines the causal interrelationships among the contemporaneous variables. The system is identified provided that there are $n(n-1)/2$ zero restrictions on $\mathbf{A}_0$. For any just-identified system, $\mathbf{A}_0$ can be rendered lower triangular by selecting the appropriate order of the variables $\mathbf{Y}$ along with the conformable order the rows of $\mathbf{A}_0$. This is the *recursive* (or *Wold causal*) *order*.

Starting with the SVAR as the data-generating process (DGP), premultiplying by $\mathbf{A}_0^{-1}$ yields the reduced-form or VAR:[4]

(2) $$\mathbf{Y}_t = \mathbf{A}_0^{-1}\mathbf{A}(L)\mathbf{Y}_{t-1} + \mathbf{A}_0^{-1}\mathbf{E}_t = \mathbf{B}(L)\mathbf{Y}_{t-1} + \mathbf{U}_t .$$

If we *knew* $\mathbf{A}_0$, then recovery of the SVAR (equation 1) from the easily estimated VAR (equation 2) would be straightforward. There are, however, a large number of $n \times n$ matrices, $\mathbf{P}_i$ that may be used to premultiply equation (2) such that the covariance matrix $\boldsymbol{\Omega} = E(\mathbf{P}_i^{-1}\mathbf{U}(\mathbf{P}_i^{-1}\mathbf{U})')$ is diagonal. Let $\mathbf{P} = \{\mathbf{P}_i\}$ be the set of all such orthogonalizing transformations.

For each ordering of the variables in $\mathbf{Y}$, there is a unique lower triangular $\mathbf{P}_i \in \mathbf{P}$ such that $\mathbf{P}_i\mathbf{P}_i' = \boldsymbol{\Omega}$. This is the Choleski decomposition of the covariance matrix and corresponds to a Wold causal ordering of the variables. Since the ordering of the variables in $\mathbf{Y}$ is arbitrary, there are as many such orderings as there are permutations of the elements of $\mathbf{Y}$. Each such ordering is just-identified and, therefore, observationally equivalent. There are also other overidentified causal orderings – that is $\mathbf{P}_i$ for which there are more than $n(n-1)/2$ zero restrictions.

The central identification problem for SVARs is to choose the one member of $\mathbf{P}$ that corresponds to the data-generating process: that is, to choose $\mathbf{P}_i = \mathbf{A}_0$ when $\mathbf{A}_0$ is unknown. The other elements can be thought of as defining pseudo-SVARs. But on what basis should we choose? There are at least two options. First, we can appeal to economic theory to tell us what the causal order should be. This is, in fact, what almost all practitioners of VAR methodologies profess to do. Unfortunately, formal economic

[4] This and the next six paragraphs are closely based on Hoover (2005).

theory is rarely decisive about causal order. So, VAR practitioners either choose the order arbitrarily, sometimes with an accompanying claim that their results are robust to alternative causal orderings – apparently unaware that such robustness arises in just those cases that the contemporaneous terms are unimportant. Or they appeal, not so much to theory, as to "just so" stories: intuition or commonsense tells them that, say, financial markets adjust more quickly than goods markets, so that interest rates, for instance, ought to be causally ordered ahead of real GDP. It is usually easy, however, to tell a "just so" story to justify almost any order – the time order of variables that are contemporaneously related at the given frequency of observation being especially unreliable. There is a special irony that this strategy should be so commonly accepted among VAR practitioners. After all, Sims's (1980) motivation in initiating the VAR program was to avoid the need to appeal to "incredible identifying restrictions."

Graph-theoretic causal search provides a second method of choosing $\mathbf{P}_i$, very much in the spirit of Hendry's general-to-specific model selection. In a causal graph, arrows connecting causal variables to their effects represent causal relationships. Spirtes et al. (2000) and Pearl (2000) show that there are isomorphisms between graphs and the probability distributions of variables. In particular, certain graphical patterns imply certain relationships of conditional independence and dependence among the variables. The graph of the DGP can also be represented through the restrictions on $\mathbf{A}_0$. Working backwards from statistical measures of conditional independence and dependence, it is possible to infer the class of graphs compatible with the data. Sometimes that class has only a single member, and then $\mathbf{A}_0$ can be identified statistically.

The key ideas of the graph-theoretic approach are simple. Suppose that $A \rightarrow B \rightarrow C$ (that is, A causes B causes C). A and C would be dependent, but conditional on B, they would be independent. Similarly for $A \leftarrow B \leftarrow C$. In each case, B is said to *screen* A from C. Suppose that $A \leftarrow B \rightarrow C$. Then, once again A and C would be dependent, but conditional on B, they would be independent. B is said to be the *common cause* of A and C. Now suppose that A and B are independent conditional on sets of variables that exclude C or its descendants, and $A \rightarrow C \leftarrow B$, and none of the variables that cause A or B directly causes C. Then, conditional on C, A and B are dependent. C is called an *unshielded collider* on the path *ACB*. (A *shielded* collider would have a direct link between *A* and *B*.)

Causal search algorithms use a statistical measure of independence, commonly a measure of conditional correlation, to check systematically the patterns of conditional independence and dependence and to work backwards to the class of admissible causal structures. In this paper, we use the PC algorithm, the most common of the causal-search algorithms (Sprites *et al.* 2000, pp. 84-85, Pearl 2000, pp. 49-51, Cooper 1999, p. 45, figure 22). It assumes that graphs are *acylical* or strictly recursive, which rules out simultaneity. While this is restrictive, it is nonetheless more general than the limiting SVARs to Choleski orders, which remain the default in most VAR studies.

The details of the PC algorithm are described in Demiralp and Hoover (2003). Essentially, it begins with the complete set of variables in the VAR densely connected by undirected edges, represented as lines in a graph without arrowheads. It then tests for unconditional correlations and removes any uncorrelated edges. It then tests for correlations conditional on one other variable, again removing edges for which correlations vanish on conditioning. It then proceed to conditioning on two, three, . . . variables. The result is an undirected *skeleton*. The algorithm begins orienting edges by seeking triples of linked variables ($A — B — C$) in which the variables on the endpoints (*A* and *C*) are independent on some conditioning set, but become dependent when conditioning on the intermediate variable (*B*). This is the pattern of an unshielded collider, and the edges are then oriented ($A \rightarrow B \leftarrow C$). Some edges may be oriented *logically* (rather than statistically), based on maintaining the assumption of acyclicality and avoiding implying the existence of unshielded colliders not identified statistically.

Not all causal graphs are recoverable from the probability distribution. Graphs that have the same unshielded colliders and the same skeleton are observationally equivalent (Pearl 2000, p. 19). If the true graph is a member of an observationally equivalent set, the algorithm will not orient the edges that distinguish one member of the set from another. In these cases, unoriented edges can be oriented in either direction without changing the likelihood, provided that no new unshielded colliders or cyclicality is introduced. Also, the maintained assumption of acyclicality notwithstanding, the algorithm will sometimes identify edges as bidirectional as a result of either ambiguity in the statistical test because of small samples, omitted latent variables, or simultaneity.

Following Swanson and Granger (1997), we treat the estimated errors ($\hat{\mathbf{U}}_t$) from the VAR in equation (2) as the original data purged of their dynamics. The covariance matrix of these transformed data ($\hat{\Omega}$) provides the necessary data for computing the various conditional correlations required by the PC algorithm. The algorithm selects a graph that best represents the causal order, and this graph in turn corresponds to particular zeroes in (and overidentifying restrictions on) $\mathbf{A}_0$.

Demiralp and Hoover (2003) provide Monte Carlo evidence that shows that the PC algorithm is highly effective at recovering the skeleton of the DGP graph and moderately effective at recovering the directions of individual links, provided that signal-to-noise ratios are high enough. Demiralp, Hoover, and Perez (2007) develop and validate a bootstrap procedure to assess the effectiveness of the closely related SGS algorithm. The procedure constructs many simulations of the VAR, equation (2), based on the actual coefficient estimates ($\hat{\mathbf{B}}(L)$) and resampling of the columns of $\hat{\mathbf{U}}_t$, runs the search algorithm, and keeps track of the distribution of edges in the resulting graphs. The bootstrap method is essentially heuristic and provides guidance for more formal investigation of the overidentifying restrictions on $\mathbf{A}_0$.

Once we have selected $\mathbf{A}_0$ as the orthogonalizing transformation to transform the VAR, equation (2), into the SVAR, equation (1), then we can appeal to Krolzig's (2003) evidence for the effectiveness of *PcGets* at locating the true restrictions on the lagged coefficients – that is, the placement of zeroes in the matrix $\mathbf{A}(L)$.

3. Data

The data consist of ten monthly series that run from 1990:02 to 2005:03. Sources and details are provided in Appendix A. Our main interest is in M2 and its role in the transmission mechanism. M2 is represented by its active component, (the logarithm of) liquid deposits (*LIQDEP*). Following the considerations of the Monetary and Reserve Analysis Section discussed in section 1, the principal factors related to liquid deposits are core CPI inflation (*COREINF*) and a monthly proxy for real GDP, (the logarithm of) industrial production (*IP*). The additional considerations of the equity market are represented by (the logarithm of) the S&P 500 stock market index (*SP500*), its price-earnings ratio (*SPPE*), and stock market volatility (*VOL*). Mortgage activity is represented by (the logarithm of) an index of mortage refinancing (*REFI*) and the interest rate on 30-year fixed-rate mortgages (*MORG30*). Monetary policy is represented by the Federal funds rate (*FF*). The long mortgage rate, the Federal funds rate, and the opportunity cost of M2 (*M2OC*), which is constructed from the 3-month Treasury bill rate and the own-rate on *M2* (see Appendix A), provides a rich set of interest rates on which to assess the interest-rate channel and the role of the yield curve in the transmission process.

As a preliminary, the data were graphed and tested for nonstationarity. Dickey-Fuller tests (with a constant and a trend), indicate that each of the series is very likely I(1), although for industrial production the test was borderline, and the series may even be better described as I(2).

4. Contemporaneous Causal Order

Our first task in establishing the contemporaneous causal order among our variables is to estimate the unrestricted VAR – that is, equation (2), where $\mathbf{Y}_t$ = [*COREINF, MORG30, LIQDEP, IP, SPPE, SP500, M2OC, REFI, VOL, FF*]′. The corrected Akaike Information Criterion of Hurwich and Tsai (1991), which seems well-adapted to this problem, selects a lag length of one. Both the Hannan-Quinn and Schwarz criteria also select only a single lag. However, all of these tests impose the same lag length on all equations. And, since in a later step, we intend to search for parsimonious, variable-specific dynamics, we should not be too restrictive at this stage. Therefore, we set the lag length to five, which will allow four lagged differences when we later construct error-correction specifications. We estimate the VAR and obtain the covariance matrix of $\hat{\mathbf{U}}_t$, using it as the input into the PC algorithm, with a critical value of 10 percent for tests of conditional correlation, a value suggested by Spirtes *et al.* (1994, pp. 103-107) for the number of available observations (177 after accounting for lags).

The algorithm selects the graph in Figure 1. While one should not read too much into the contemporaneous structure, since many important causal channels may operate with a lag, the graph is striking in its division of the contemporaneous variables into three distinct groups: 1) mortgage-related variables, the Federal funds rate, and the opportunity cost of M2 for an undirected network; 2) stock market variables, liquid deposits, and industrial production for a highly structure network, with a bidirectional edge between the S&P 500 index and stock-market volatility; 3) core inflation is isolated contemporaneously from all other variables.

How reliable is the identified graph? To evaluate it, we apply the bootstrap procedure of Demiralp, Hoover, and Perez (2007) with 10,000 replications. The results are shown in Table 3. There are 45 possible edges among ten variables. The first three columns show the results of the PC algorithm for 14 of them – the eight selected by the algorithm and six more that are selected in 10 percent or more of the bootstrap replications. The next five columns show the actual distribution of edges from the bootstrap. The last three columns present summary statistics: *exists* is the fraction of replications in which some edge is found (= 100 – *no edge*); *directed* is the percentage of edges discovered that have a definite direction; *net direction* is the difference between the percentage of edges directed rightward (→) and edges directed leftward (←).

The bootstrap presents strong evidence in favor of the existence of the first five edges in Table 3 (*exists* greater than 90 percent), and is supportive of the direction selected by the PC algorithm in three of those cases (compare *net direction* in the last column to the edge direction in column 2). The edge between *FF* and *M2OC*, however, is equally directed in the bootstrap each way, and the edge between *LIQDEP* and *VOL* is nearly equal. The remaining three edges receive much weaker support (with *exists* at only 28 percent for the edge between *REFI* and *M2OC*), though the first two are fairly firmly oriented according to the bootstrap in direction selected by the PC algorithm. All other edges are selected in the bootstrap in less than 20 percent of the replications. We explore the problematic edges identified by the bootstrap more fully below.

A causal graph corresponds to a set of over-identifying restrictions (zero restrictions on $\mathbf{A}_0$), which can be tested. The graph in Figure 1, however, cannot be tested as is. First, the four undirected edges indicate that it represents not a single causal order, but an equivalence class of orders with equal likelihoods: each link can be directed in any way we like, so long as no new unshielded colliders or cycles are introduced. Lacking better grounds (and we acknowledge that these grounds are weak), we initially orient these links according to their net direction in the bootstrap: *REFI* ← *MORG30*, *M2OC* ← *MORG30*, *REFI* → *M2OC*. The edge between *FF* and *M2OC* is evenly directed in the bootstrap between right and left (*net direction* = 0), which would suggest a bidirectional edge. However, a rightward edge (→) would, given the other selected orientations, would introduce an unshielded collider and remove the resulting graph from the equivalence class selected by the PC algorithm. Thus, we orient it as *FF* ← *M2OC*.

The second barrier to testing the overidentifying restrictions implied by the graph is the bidirectional edge *VOL* ↔ *SP500*. When it is in the graph, the SVAR estimates return a near singular matrix. The problem is that, in the terminology of Juselius (2007, p. 208), the system is *generically*, but not *empirically* identified – that is, identification fails for particular parameter values. Consequently, we initially test the graph with the edge between *VOL* and *SP500* oriented separately in each direction.

The overidentifying assumptions implied by the graph with these further specifications is tested against a just-identified SVAR. The likelihood-ratio test of the overidentifying restrictions for the graph with *VOL* → *SP500* ($\chi^2(37)$) strongly rejects the restrictions (*p*-value of 0.0042), while the test for the graph with *VOL* ← *SP500* borderline accepts (*p*-value of 0.11) at the 10 percent critical value chosen for this study.

Since the risk, we believe, is greater of too tightly restricting the causal order, we investigate the graph further through an informal general-to-specific procedure. We supplement the graph with all of the non-selected edges shown in Table 3 – that is, with those edges that the bootstrap selects in 10 percent or more of the replications. As shown in Table 4, this model (General Model I) cannot be rejected against a just-identified SVAR (*p*-value = 0.55). The table also reports a sequence of tests in which successive edges are removed, starting with the edge with the lowest score for *exists* in the bootstrap (see Table 3), followed by the next lowest, and so on to form joint tests (tests of restrictions 1-6). While none of the joint tests can be rejected at a 10 percent size, note the large fall in the *p*-value between test 4 and test 5, suggesting that the edge *FF* ← *VOL* may be relatively more important than the others. Test 7 is the joint test of the restrictions of tests 1-6 with that edge restored. Its *p*-value nearly triples relative to test 6. In keeping with our seeking a permissive specification, we therefore retain *FF* ← *VOL* in addition to General Model I to form General Model II, which is the basis for further explorations of the specification.

The edge *REFI* — *M2OC* has the lowest score for *exists* of any edge in the graph selected by the PC algorithm. (As we have noted earlier, it has been oriented in General Models I and II. Test 8 shows that we cannot reject the omission of the oriented edge.

The edges among *REFI*, *MORG30*, and *M2OC* were, as we noted, oriented on weak grounds in specifying General Model I. Most reorientation of these edges are observationally equivalent to the ones that we have chosen. However, if the edge *REFI* — *M2OC* is omitted and both *REFI* and *M2OC* are oriented into *MORG30*, an unshielded collider is created. Test 9 rejects the restriction implied by this new unshielded collider, confirming that these two edges should be selected from the equivalence class that includes their orientation in General Model II.

Finally, consider the two edges, *IP* → *VOL* and *LIQDEP* → *SP500*, that have the second and third lowest scores for *exists* in the bootstrap. Tests 10 and 11 show that eliminating either of them can be rejected.

Figure 2 shows the final graph of the contemporaneous causal order of the SVAR that incorporates all of the considerations of our specification search. It is General Model II with the omission of *REFI* → *M2OC*. It cannot be rejected against the just-identified model (p-value = 0.20).

5. The Lag Structure

Most VAR analysis would content itself with having established the contemporaneous causal order, which is all that is needed to identify independent shocks to the various equations in the SVAR, and then proceed to compute impulse-response functions and variance decompositions. We believe, however, that more is to be learned about the dynamic causal structure about which factors are truly important. And we believe that a more careful specification of the dynamics will deliver more precise estimates of the standard errors of impulse-response functions.

Our strategy is to use *PcGets* (version 1.0; Hendry and Krolzig 2001) to select the lag structure of the model conditional on the contemporaneous causal structure (see

Krolzig 2003). Since the data are all nonstationary, we reparameterize the SVAR with unrestricted lags in a vector-error-correction form:

(3) $$\mathbf{A}_0\Delta\mathbf{Y}_t = \mathbf{A}_1(L)\Delta\mathbf{Y}_{t-1} + \mathbf{A}_2\mathbf{Y}_{t-1} + \mathbf{E}_t\,.$$

$\mathbf{A}_0$ is specified according to Figure 2 and is held fixed though all searches.

As $\Delta\mathbf{Y}_{t\text{-}1}$ is stationary, the estimates of the elements of $\mathbf{A}_1$ have standard distributions; while, since $\mathbf{Y}_{t\text{-}1}$ is nonstationary, the estimates of the elements of $\mathbf{A}_2$ have non-standard distributions and critical values need to be inflated in the direction of those provided by Dickey and Fuller (1979). *PcGets* does not allow the different critical values for different types of variables. Our strategy will be to conduct four ordinary-least-squares searches for each separate equation of the SVAR, using the default liberal and conservative settings in *PcGets*. The most important difference between these settings for our purposes is that in the primary elimination step (a *t*-test), the *liberal* setting uses a critical value of 5 percent, while the *conservative* setting uses a critical value of 1 percent, where the critical values assume a normal distribution. The conservative setting is used here as an *ad hoc* method of mimicking the higher critical values of the nonstandard distributions appropriate for nonstationary variables. Our four searches are:

1. A liberal search in which only the contemporaneous specification (i.e., the appropriate elements of $\mathbf{A}_0$) are held fixed.
2. A conservative search in which, as well as the contemporaneous terms, the short-term dynamics selected in Search 1 (the specification of $\mathbf{A}_1$ – the placement of zeroes in the matrix, but not the estimates of the elements) are held fixed.
3. A conservative search in which only the contemporaneous terms are held fixed.
4. A liberal search in which the long-run dynamics selected in Search 3 (the specification of $\mathbf{A}_2$) are held fixed.

The specification with the lowest Akaike information criterion is chosen, conditional for Search 1 on all the estimates of the relevant elements of $\mathbf{A}_2$ displaying *t*-statistics greater than 2.6.

The detailed specification of the SVAR estimated as a system using a seemingly unrelated regressions (SUR) estimator is reported in Appendix B. (The SUR estimator guarantees that the estimated covariance matrix $\hat{\mathbf{\Sigma}} = \mathrm{E}(\hat{\mathbf{E}}\hat{\mathbf{E}}')$ be diagonal.) The Wald test for the restrictions implied in this model against a just-identified model in which it is nested yields is distributed is a $\chi^2(437)$ test with a *p*-value = 0.35: we cannot reject the fully specified model at any conventional size.[5] The complete causal order is summarized in Table 5. To get an idea of how much detail about the causal process that our investigation has uncovered, how parsimonious our final specification is, consider what Table 5 would look like for any typical Choleski ordering: every cell on the main-diagonal and above would be filled in as light grey (indicating the presence of lagged variables) and every cell below the main diagonal in black (indicating the presence of contemporaneous and lagged variables). The overall lighter tone, especially the white (empty) cells, reveals that we have stripped away large numbers of redundant regressors.

6. The Role of M2 in the Monetary Transmission Process

We are now in a position to return to the business of the Monetary and Reserve Analysis Section. Table 5 is concerned with direct effects or proximate causes. The discussion in Section 1, suggests that the entire *LIQDEP* row should be filled, indicating that each of the other variables is either a contemporaneous or lagged cause of *LIQDEP*. But we have discovered the surprising fact that none of the central quantity-theoretic variables, *COREINF, IP*, nor *M2OC*, nor lagged *LIQDEP* itself is a direct cause of *LIQDEP*. *M2OC* is the difference between the 3-month Treasury-bill rate and the own-rate of return on M2 – both short rates. The other interest rates, *MORG30* and *FF*, are direct causes of *LIQDEP*. This is consistent with some theories of money demand (for example Keynes's (1936, ch. 15) theory of liquidity preference) that imply that money should be sensitive to the difference between short rates (e.g., *FF*) and long rates of interest (e.g., *MORG30*), rather than to a short rate alone. The "special factors," with the exception of stock market volatility (*VOL*) are selected as direct causes of *LIQDEP*. A pitfall of many statistical studies is to mistake causation for correlation. The pit is quite deep here, as *LIQDEP* is identified as a direct cause of each of the other variables except for *REFI* and *FF*.

Another pitfall of single-equation and correlational studies is the mixing of direct and indirect causes, which can be distinguished explicitly in a VAR system. Figure 3 displays the impulse-response functions for *LIQDEP* to one-standard-deviation

[5] While all just-identified models have the same likelihood, our selected model is not nested in every just-identified model. It is nested, among others, in one with the Choleski ordering [*COREINF, MORG30, LIQDEP, IP, SPPE, SP500, M2OC, REFI, VOL, FF*].

temporary shock to each of the other variables.[6] Consider the three variables that were excluded as direct causes of *LIQDEP*: A shock to core inflation (column 1, row 2) quickly has a significant positive effect on *LIQDEP*, but is soon offset by a smaller, borderline significant negative effect, the cumulative effect remaining positive for six months after the shock. A shock to industrial production (column 1, row 3) has a negative effect in period 3, followed by a less-than-offsetting positive effect in period 4; but, in subsequent periods, the effect turns significantly and enduringly negative – not the effect that the causal theorist would expect. The casual theorist is again challenged by the effect of a shock to *M2OC*, which, though initially negative, becomes a more-than-offsetting and long-lived effect in subsequent periods. The remainder of the impulse-response functions indicate that "special factors" – just as they did with direct effects – tend to be statistically significant causes of *LIQDEP* in the short-run, but to dwindle toward zero or, at the least, toward statistical insignificance at longer horizons.

While most of the considerations concerning the relationship of M2 to other variables in section 1 are discussed from the point of view of the demand for money, the real importance of M2 to the Federal Reserve is found in its place in the transmission mechanism for monetary policy, in which M2 is a cause rather than an effect. Figure 4, therefore, turns the tables and considers the effects of one-standard deviation shock to *LIQDEP* on the other variables. The pattern of the impulse-response functions is similar for all of the variables. The largest effects occur in the first six months to a year and are oscillatory. While a few of the impulse-response functions remain statistically significant at longer horizons, the effects become very small after a year.

While the evidence tends to bear against *LIQDEP* (or M2) being substantial linkage in the transmission mechanism, it is difficult to quantify its importance with Figure 4, since there is no natural metric on which to compare the different effects of *LIQDEP*. In order to get a better handle on the role of *LIQDEP* in the transmission mechanism, we concentrate on the effects of a shock to the Federal funds rate (*FF*), the Federal Reserve's main policy variable. We consider a permanent, 25-basis-point shock, since this is by far the Federal Reserve's most common monetary policy action in

[6] Since the VAR is specified in a VECM form, a temporary shock is a positive shock followed by equal negative shock in the next period.

practice.[7] And since the Fed is principally concerned with the effects of its policies on growth and inflation, we focus on responses of core inflation (*COREINF*) and industrial production (*IP*) to the monetary-policy shock. Figure 5 displays the ordinary impulse-response functions (and their accumulations) as well as impulse-response functions where *LIQDEP* has been shut down by setting its value to zero in all equations and all periods. The difference between these two impulse-response functions is a measure of the role of *LIQDEP* in the transmission mechanism.

The evidence of Figure 5 is that M2 (or *LIQDEP*) plays an almost immeasurably small role in the transmission mechanism. The maximum difference between the impulse-response functions for *COREINF* occurs at period 4 (Figure 5.A, top panel) and is less that a tenth of percentage point on the inflation rate. And the two impulse-response functions are nowhere statistically distinguishable in the sense that both lie within the standard-error bands for the function with *LIQDEP*.

The differences between the two impulse-response functions for *IP* (Figure 5.B, top panel) are similarly small, at most less than one-tenth of a percent on the growth rate of industrial production, as is the difference between the cumulated impulse-response functions (bottom panel). And this difference is unlikely to be statistically significant as, again, both of the uncumulated functions lie within the standard-error bands of the impulse-response function with *LIQDEP*.

7. Conclusions

Our investigation is both methodological and substantial. Methodologically, it provides a concrete illustration of how to coordinate the graph-theoretic causal-search algorithms, previously applied to vector autoregressions by a number of investigators, with David Hendry's general-to-specific search methodology embodied in *PCGets* to identify empirically a structural econometric model in a case in which theory is relatively weak and not a reliable source of identifying restrictions. Typically, investigators use the PC algorithm or one of its relatives to select a contemporaneous causal graph. We showed how to use the bootstrap techniques developed by Demiralp, Hoover, and Perez to assess the uncertainties associated with selecting such a graph. These techniques proved

[7] A permanent shock in the VECM form is a positive shock in the first period with no shocks in subsequent periods.

invaluable guiding an informal general-to-specific search using test of overidentifying restrictions to select a contemporaneous causal order for the SVAR in which we could have reasonable confidence. One avenue for future development would be to provide a more formally developed search procedure along these lines. In applying *PCGets* to nonstationary data, we adopted what we believe to be an effective, though *ad hoc*, procedure to ensure that appropriate selection criteria were applied to the I(1) as well as the I(0) terms. Another future development would be to extend *PCGets* to do this automatically.

One weakness in our determination of the causal order is the presence in our case study of undirected edges in the initial graph, which are indicators of observationally equivalent causal orderings. While we were able to resolve the observational equivalence to some degree through enrichment of the specification, some of our choices remained arbitrary. It is possible that these may be resolved in some cases using the invariance methods for discovering causal order as discussed by Hoover (2001, chapters 7-9).

On the substantial side, we were able to provide a carefully tested fully identified model of the role of M2 in the transmission mechanism in which the informal assumptions of the Federal Reserve's Monetary and Reserve Analysis Section could be assessed. On the positive side, the evidence supports the section's identification of particular "special factors" connected to the behavior of M2. On the negative side, the quantity-theoretic core of their analysis seems to be largely at odds with the data. What is more, the rationale for focusing attention on M2 is undermined by evidence that it plays an insignificant role in the transmission of monetary policy. This is in keeping with other recent findings about M2 (Hale and Jordá 2007). Some economists have argued that while M2 has only a small role in the substantive transmission of monetary policy, it nonetheless conveys significant information about the state of the monetary economy in much the same way that a barometer, while not a causal linkage in weather systems, nonetheless provides useful information (see Dotsey and Otrok (1994) for a survey of views). Our conclusions are different. Once we have such a detailed causal identification, we can see that M2 does play a real causal role (*LIQDEP* is identified as a cause of seven of nine nonpolicy variables in our system), but that it is a practically insignificant one. Our identified model conveys fuller information – serves as a better barometer – than M2 can.

Appendix A. Data

All data are monthly. If a Haver series code is given, the data were downloaded from Haver Analytics *United States Economic Statistics* database, version date 3 June 2005. Natural logarithms indicated by "log."

COREINF = 1200[(log($corecpi_t$) – log(($corecpi_{t-1}$)], where *corecpi* = Consumer Price Index less Food and Energy. Source: Bureau of Labor Statistics [Haver: *pcuslfe*]. Units: Index 1982-84 = 100; seasonally adjusted.

FF = Effective Federal Funds Rate. Source: Federal Reserve [Haver: *ffed*]. Units: annual yield to maturity (percent per annum).

IP = log(*industrial production index*). Source: Federal Reserve [Haver: *ip*]. Units: index 1997=100; seasonally adjusted.

LIQDEP = log(*liquid deposits*), *liquid deposits* = Demand Deposits + Other Checkable Deposits + Small Denomination Time Deposits, including Money Market Deposit Accounts. Source: Federal Reserve. Units: millions of dollars; seasonally adjusted.

M2OC = Opportunity Cost of Holding M2 = 3-month Treasury Bill less M2 Own Rate. Source: Federal Reserve (Division of Monetary Affairs, Reserve Analysis Division). Units: annual yield to maturity (percent per annum). [3-month Treasury Bill: Source: Federal Reserve. M2 Own Rate = weighted average of yields on deposits. Source for underlying yields: *Bank Rate Monitor*.]

MORG30 = Interest Rate on 30-year Mortgages. Source: Federal Mortgage Acceptance Corporation, Primary Market Survey: 30-year Fixed Rate Mortgages [Haver: *frm30*]. Units: annual yield to maturity (percent per annum).

REFI = log(*mortage refinance*). Source: Mortgage Banker's Association. Units: index 1990 = 100

SVOL = log(*volatility*), where *volatility* = VIX (up to August 2003), renamed VXO thereafter (both are measure of implied volatitlity based on the S&P 100 Index (OEX) option prices. Source: Chicago Board Options Exchange Units: percent.

SP500 = log(*s&p 500 stock index*) Source: *Wall Street Journal* [Haver: *sp500*]. Units: index 1941-43 = 10.

SPPE = S&P 500 Price-Earnings Ratio. Source: Standard & Poors (http://www2.standardandpoors.com/spf/xls/ondex/SP500EPSEST.XLS) Units: ratio.

(Note: in the final version, this appendix will be made more attractive and user-friendly.)

Appendix B. Estimates of the Final Specification

System: RESTRICTED
Estimation Method: Seemingly Unrelated Regression
Date: 06/06/07 Time: 15:11
Sample: 1990M07 2005M03
Included observations: 177
Total system (balanced) observations 1770
Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
C(15)	-1.315780	0.499751	-2.632872	0.0085
C(23)	-39.37165	16.73529	-2.352613	0.0188
C(34)	1.832289	0.452049	4.053299	0.0001
C(51)	-1.153074	0.067605	-17.05604	0.0000
C(52)	0.577003	0.148787	3.878051	0.0001
C(54)	1.734408	0.620376	2.795739	0.0052
C(56)	-1.224759	0.287838	-4.255022	0.0000
C(58)	-0.988009	0.246309	-4.011263	0.0001
C(59)	0.539723	0.149133	3.619064	0.0003
C(61)	-23.41776	9.507006	-2.463210	0.0139
C(67)	0.027511	0.051158	0.537768	0.5908
C(69)	0.359405	0.054532	6.590774	0.0000
C(78)	0.180557	0.051634	3.496866	0.0005
C(80)	7.216779	1.750468	4.122771	0.0000
C(98)	0.637482	0.255262	2.497367	0.0126
C(100)	0.228969	0.060022	3.814747	0.0001
C(113)	-0.081101	0.014308	-5.668152	0.0000
C(119)	0.141556	0.024508	5.775852	0.0000
C(120)	0.045918	0.013315	3.448658	0.0006
C(122)	-0.271640	0.076260	-3.562038	0.0004
C(137)	0.009890	0.001955	5.057726	0.0000
C(141)	-0.146036	0.063289	-2.307427	0.0212
C(143)	0.175356	0.062167	2.820752	0.0048
C(145)	0.290048	0.076447	3.794095	0.0002
C(157)	0.026878	0.009405	2.857830	0.0043
C(159)	0.034130	0.009075	3.760969	0.0002
C(174)	-0.001221	0.000330	-3.704182	0.0002
C(175)	-0.064287	0.011705	-5.492087	0.0000
C(177)	-0.006106	0.001184	-5.156189	0.0000
C(178)	0.005183	0.001534	3.377611	0.0007
C(179)	0.015933	0.003265	4.880087	0.0000
C(181)	-0.005033	0.001122	-4.484622	0.0000

C(183)	0.257149	0.042055	6.114667	0.0000
C(201)	-0.007808	0.001599	-4.884491	0.0000
C(212)	0.003487	0.001031	3.380552	0.0007
C(218)	0.033415	0.008783	3.804511	0.0001
C(227)	-0.003941	0.001261	-3.124461	0.0018
C(230)	-0.000662	0.000217	-3.048724	0.0023
C(238)	0.008137	0.000644	12.63333	0.0000
C(240)	0.001792	0.000704	2.545773	0.0110
C(242)	0.005737	0.000651	8.806786	0.0000
C(244)	-0.103567	0.010846	-9.548661	0.0000
C(253)	-0.806358	0.056956	-14.15747	0.0000
C(259)	-0.141061	0.069624	-2.026056	0.0429
C(274)	-0.229424	0.061511	-3.729803	0.0002
C(278)	-0.164174	0.068290	-2.404083	0.0163
C(287)	-0.309694	0.057485	-5.387362	0.0000
C(290)	-0.263573	0.076893	-3.427803	0.0006
C(299)	-0.119678	0.028501	-4.199116	0.0000
C(300)	0.134112	0.035766	3.749741	0.0002
C(303)	-0.090781	0.026954	-3.367958	0.0008
C(305)	1.054727	0.365734	2.883865	0.0040
C(308)	8.976596	2.101105	4.272322	0.0000
C(312)	-1.659758	0.296174	-5.603991	0.0000
C(325)	-6.824290	2.005694	-3.402459	0.0007
C(328)	5.912745	2.278565	2.594942	0.0095
C(347)	0.163074	0.066042	2.469248	0.0136
C(358)	5.948801	0.928889	6.404214	0.0000
C(359)	-1.699260	0.253240	-6.710066	0.0000
C(361)	-0.559205	0.065795	-8.499209	0.0000
C(362)	-0.937799	0.173526	-5.404370	0.0000
C(363)	-0.174746	0.037779	-4.625506	0.0000
C(366)	5.774195	1.125595	5.129905	0.0000
C(370)	-1.830178	0.462823	-3.954377	0.0001
C(376)	0.014412	0.001346	10.70972	0.0000
C(377)	0.006302	0.002310	2.727669	0.0064
C(378)	0.003740	0.001495	2.500994	0.0125
C(393)	0.017711	0.006891	2.570247	0.0102
C(395)	0.025313	0.007466	3.390607	0.0007
C(397)	-0.063803	0.010583	-6.028647	0.0000
C(403)	0.210253	0.060406	3.480668	0.0005
C(414)	0.002259	0.001158	1.950759	0.0513
C(415)	-0.008551	0.001529	-5.590950	0.0000
C(416)	-0.002172	0.001197	-1.815558	0.0696
C(417)	-0.008738	0.003028	-2.885499	0.0040
C(418)	0.013378	0.003189	4.195268	0.0000
C(421)	-0.022513	0.007384	-3.049053	0.0023
C(423)	-0.015354	0.008084	-1.899405	0.0577
C(424)	-0.028522	0.006664	-4.280176	0.0000

C(425)	-0.025589	0.007244	-3.532274	0.0004
C(426)	0.001231	0.000526	2.340792	0.0194
C(427)	0.439574	0.111727	3.934363	0.0001
C(436)	0.397373	0.045286	8.774752	0.0000
C(442)	0.184542	0.064194	2.874746	0.0041
C(443)	0.218691	0.065683	3.329472	0.0009
C(460)	0.136565	0.060594	2.253780	0.0243
C(463)	1.026048	0.311910	3.289566	0.0010
C(467)	-0.246939	0.073740	-3.348768	0.0008
C(471)	0.140770	0.050919	2.764608	0.0058
C(480)	3.172151	0.849387	3.734634	0.0002
C(481)	-0.881909	0.235022	-3.752451	0.0002
C(483)	-0.338881	0.059513	-5.694186	0.0000
C(484)	-0.425942	0.155639	-2.736724	0.0063
C(485)	-0.191347	0.036135	-5.295277	0.0000
C(486)	0.041922	0.017392	2.410380	0.0160
C(488)	2.225890	1.287897	1.728313	0.0841
C(531)	0.326984	0.066919	4.886253	0.0000
C(541)	-4.288574	1.187197	-3.612351	0.0003
C(542)	0.858993	0.324735	2.645209	0.0082
C(544)	0.287543	0.088413	3.252265	0.0012
C(545)	0.738747	0.218957	3.373944	0.0008
C(546)	0.141847	0.047232	3.003166	0.0027
C(547)	-0.089237	0.025263	-3.532336	0.0004
C(549)	1.735007	1.764275	0.983411	0.3255
C(563)	0.104322	0.050163	2.079686	0.0377
C(567)	-1.871283	0.541897	-3.453208	0.0006
C(572)	-3.080963	16.74056	-0.184042	0.8540
C(576)	-0.439573	0.369547	-1.189492	0.2344
C(580)	-2.236222	0.520611	-4.295378	0.0000
C(584)	-13.39220	2.871737	-4.663451	0.0000
C(593)	-0.701121	0.468105	-1.497786	0.1344
C(597)	0.103387	0.061406	1.683673	0.0924
C(598)	0.375377	0.072342	5.188891	0.0000
C(601)	-0.458602	0.146596	-3.128332	0.0018
C(602)	8.759327	2.026037	4.323380	0.0000
C(603)	-5.187173	1.438018	-3.607169	0.0003
C(606)	-0.122639	0.023240	-5.277054	0.0000
C(610)	40.87992	13.65042	2.994775	0.0028

Determinant residual covariance		9.83E-23

Equation: DCOREINF=C(15)*DFF(-1)+C(23)*DLLIQDEP(-1)+C(34)
*DLSP100VOL(-4)+C(51)*COREINF(-1)+C(52)*FF(-1)+C(54)
*LLIQDEP(-1)+C(56)*LSP100VOL(-1)+C(58)*M2OC(-1)+C(59)
*MORG30(-1)+C(61)
Observations: 177

R-squared	0.636361	Mean dependent var	-0.011461
Adjusted R-squared	0.616764	S.D. dependent var	1.613443
S.E. of regression	0.998820	Sum squared resid	166.6060
Durbin-Watson stat	2.019333		

Equation: DFF=C(67)*DLSP100VOL+C(69)*DM2OC+C(78)*DFF(-3)
+C(80)*DLIP(-1)+C(98)*DLSP500(-3)+C(100)*DM2OC(-1)+C(113)
*FF(-1)+C(119)*M2OC(-1)+C(120)*MORG30(-1)+C(122)
Observations: 177

R-squared	0.688741	Mean dependent var	-0.031977
Adjusted R-squared	0.671966	S.D. dependent var	0.193356
S.E. of regression	0.110743	Sum squared resid	2.048088
Durbin-Watson stat	1.980576		

Equation: DLIP=C(137)*DFF(-1)+C(141)*DLIP(-1)+C(143)*DLIP(-3)
+C(145)*DLLIQDEP(-1)+C(157)*DLSP500(-1)+C(159)*DLSP500(
-3)+C(174)*FF(-1)+C(175)*LIP(-1)+C(177)*LREFI(-1)+C(178)
*LSP100VOL(-1)+C(179)*LSP500(-1)+C(181)*MORG30(-1)
+C(183)
Observations: 177

R-squared	0.463391	Mean dependent var	0.002374
Adjusted R-squared	0.424127	S.D. dependent var	0.005161
S.E. of regression	0.003916	Sum squared resid	0.002515
Durbin-Watson stat	2.026385		

Equation: DLLIQDEP=C(201)*DFF(-4)+C(212)*DLREFI(-3)+C(218)
*DLSP500(-1)+C(227)*DMORG30(-2)+C(230)*DSPPE(-1)+C(238)
*LREFI(-1)+C(240)*LSP500(-1)+C(242)*MORG30(-1)+C(244)
Observations: 177

R-squared	0.748052	Mean dependent var	0.005898
Adjusted R-squared	0.736054	S.D. dependent var	0.006635
S.E. of regression	0.003409	Sum squared resid	0.001952
Durbin-Watson stat	2.021723		

Equation: DLREFI=C(253)*DMORG30+C(259)*DFF(-1)+C(274)
*DLREFI(-4)+C(278)*DLSP100VOL(-4)+C(287)*DMORG30(-1)
+C(290)*DMORG30(-4)+C(299)*LREFI(-1)+C(300)*LSP100VOL(
-1)+C(303)*MORG30(-1)+C(305)
Observations: 177

R-squared	0.685868	Mean dependent var	0.015268
Adjusted R-squared	0.668939	S.D. dependent var	0.258963
S.E. of regression	0.149002	Sum squared resid	3.707661
Durbin-Watson stat	2.020908		

Equation: DLSP100VOL=C(308)*DLIP+C(312)*DLSP500+C(325)*DLIP(
-2)+C(328)*DLLIQDEP(-1)+C(347)*DM2OC(-4)+C(358)*LIP(-1)
+C(359)*LLIQDEP(-1)+C(361)*LSP100VOL(-1)+C(362)*LSP500(
-1)+C(363)*M2OC(-1)+C(366)
Observations: 177

R-squared	0.367702	Mean dependent var	-0.001812
Adjusted R-squared	0.329612	S.D. dependent var	0.159814
S.E. of regression	0.130852	Sum squared resid	2.842277
Durbin-Watson stat	2.078183		

Equation: DLSP500=C(370)*DLLIQDEP+C(376)*DSPPE+C(377)
*DCOREINF(-1)+C(378)*DCOREINF(-2)+C(393)*DLREFI(-1)
+C(395)*DLREFI(-3)+C(397)*DLSP100VOL(-1)+C(403)*DLSP500(
-3)+C(414)*DSPPE(-2)+C(415)*DSPPE(-3)+C(416)*DSPPE(-4)
+C(417)*COREINF(-1)+C(418)*FF(-1)+C(421)*LREFI(-1)+C(423)
*LSP500(-1)+C(424)*M2OC(-1)+C(425)*MORG30(-1)+C(426)
*SPPE(-1)+C(427)
Observations: 177

R-squared	0.621054	Mean dependent var	0.006772
Adjusted R-squared	0.577883	S.D. dependent var	0.034191
S.E. of regression	0.022214	Sum squared resid	0.077968
Durbin-Watson stat	1.975053		

Equation: DM2OC=C(436)*DMORG30+C(442)*DFF(-1)+C(443)*DFF(-2)
+C(460)*DLSP100VOL(-3)+C(463)*DLSP500(-2)+C(467)*DM2OC(
-2)+C(471)*DMORG30(-2)+C(480)*LIP(-1)+C(481)*LLIQDEP(-1)
+C(483)*LSP100VOL(-1)+C(484)*LSP500(-1)+C(485)*M2OC(-1)
+C(486)*MORG30(-1)+C(488)
Observations: 177

R-squared	0.477115	Mean dependent var	-0.003672
Adjusted R-squared	0.435412	S.D. dependent var	0.161099
S.E. of regression	0.121048	Sum squared resid	2.388390
Durbin-Watson stat	1.908978		

Equation: DMORG30=C(531)*DMORG30(-1)+C(541)*LIP(-1)+C(542)
*LLIQDEP(-1)+C(544)*LSP100VOL(-1)+C(545)*LSP500(-1)
+C(546)*M2OC(-1)+C(547)*MORG30(-1)+C(549)
Observations: 177

R-squared	0.235873	Mean dependent var	-0.023898
Adjusted R-squared	0.204222	S.D. dependent var	0.204845
S.E. of regression	0.182735	Sum squared resid	5.643241
Durbin-Watson stat	1.865710		

Equation: DSPPE=C(563)*DCOREINF(-4)+C(567)*DFF(-4)+C(572)
*DLLIQDEP(-1)+C(576)*DLREFI(-1)+C(580)*DLSP100VOL(-1)
+C(584)*DLSP500(-3)+C(593)*DMORG30(-2)+C(597)*DSPPE(-2)
+C(598)*DSPPE(-3)+C(601)*FF(-1)+C(602)*LIP(-1)+C(603)
*LLIQDEP(-1)+C(606)*SPPE(-1)+C(610)
Observations: 177

R-squared	0.404150	Mean dependent var	0.021186
Adjusted R-squared	0.356628	S.D. dependent var	1.411692
S.E. of regression	1.132324	Sum squared resid	208.9919
Durbin-Watson stat	2.097818		

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Table 1
Growth Rates of M2 and Its Major Components
(percent per annum)

	M2	**Liquid Deposits**	**Small Time Deposits**	**M2 Money Funds**	**Currency**	**Nominal GDP**	**Inflation**[1]
2004:2	9.7	17.1	-4.6	-7.2	4.0	6.6	4.7
2004:Q3	2.7	4.5	1.8	-11.3	9.3	5.1	6.2
October 2004	2.5	6.1	3.3	-20.2	4.2		
November 2004	6.3	8.0	5.1	-5.7	9.9		

Source: Board of Governors of the Federal Reserve System and Bureau of Economic Analysis.
[1]Measured by the personal consumption expenditure deflator.

Table 2
Contributions of M2 Components to M2 Growth

	2004:2	**2003:3**	**October 2004**	**November 2004**
M2	9.7	2.7	2.5	6.3
Liquid Deposits	10.8	2.9	4.0	5.2
MMMF	-0.9	-1.4	-2.3	-0.6
Small Time	-0.6	0.2	0.4	0.6
Currency	0.4	1.0	0.5	1.1

Source: Board of Governors of the Federal Reserve System.
Components may not sum to total because traveler's checks are not shown.

Table 3
Bootstrap Evaluation of the Causal Graph

Causal Order Selected by the PC Algorithm[1]			Edge Identification (percent of bootstrap realizations)[2]					Summary Statistics for Bootstrap Distribution[3]		
			—	←	no edge	→	↔	exists	directed	net direction
REFI	—	*MORG30*	64	21	0	13	3	100	36	-8
SP500	←	*SPPE*	18	52	0	10	21	100	82	-42
FF	—	*M2OC*	34	24	1	25	16	99	66	0
M2OC	—	*MORG30*	47	34	3	12	4	97	52	-22
VOL	↔	*SP500*	8	23	8	25	35	92	91	2
LIQDEP	→	*SP500*	0	0	45	37	17	55	100	68
IP	→	*VOL*	2	1	54	34	9	46	96	74
REFI	—	*M2OC*	12	4	72	10	2	28	56	22
IP	no edge	*SPPE*	1	0	82	11	6	18	94	58
FF	no edge	*VOL*	0	4	84	0	11	16	99	-25
FF	no edge	*SP500*	0	2	85	0	13	15	100	-8
COREINF	no edge	*VOL*	2	1	88	8	2	12	88	63
FF	no edge	*LIQDEP*	1	1	88	6	4	12	94	41
COREINF	no edge	*SP500*	1	0	88	9	2	12	92	72

[1] 14 of 45 candidate edges; only edges that are identified as existing in more than 10 percent of the bootstrap replications are shown.

[2] Values indicate percentage of 10,000 bootstrap replications in which each type of edge is found. Based on the procedure in Demiralp, Hoover, and Perez (2007) with critical value of 2.5 percent for tests of conditional correlation (corresponding to the 10 percent critical value used in the PC algorithm).

[3] *exists* = the percentage of bootstrap replications in which an edge is selected (= 100 – no edge); *directed* = edges directed as a percentage of edges selected; *net direction* = difference between edges directed right (→) and left (←).

Table 4
Tests of Over-identifying Restrictions

	Specification	Likelihood Ratio Test against the Just-Identified Model (*p-value*)
General Model I	Graph in Figure 1 modified with *SP500* → *VOL* *REFI* ← *MORG30* *M2OC* ← *MORG30* *REFI* → *M2OC* *FF* ← *M2OC* supplemented with *IP* → *SPPE* *FF* ← *VOL* *FF* ← *SP500* *COREINF* → *VOL* *FF* → *LIQDEP* *COREINF* → *SP500*	0.55
Tests of restrictions		
1	omit *COREINF* → *SP500*	0.51
2	and omit *FF* → *LIQDEP*	0.39
3	and omit *COREINF* → *VOL*	0.37
4	and omit *FF* ← *SP500*	0.32
5	and omit *FF* ← *VOL*	0.13
6	and omit *IP* → *SPPE*	0.11
7	restore *FF* ← *VOL*	0.28
General Model II	Graph in Figure 1 modified with *FF* ← *VOL*	0.28
Tests of restrictions		
8	omit *REFI* → *M2OC*	0.20
9	and reorient as *REFI* → *MORG30* and reorient as *M2OC* → *MORG30*	0.00
10	restore *REFI* ← *MORG30* and *M2OC* ← *MORG30* omit *IP* → *VOL*	0.08
11	restore *IP* → *VOL* omit *LIQDEP* → *SP500*	0.01

Table 5
The Causal Structure of the SVAR

	Causes									
Effects	*COREINF*	*MORG30*	*LIQDEP*	*IP*	*SPPE*	*SP500*	*M2OC*	*REFI*	*VOL*	*FF*
COREINF										
MORG30										
LIQDEP										
IP										
SPPE										
SP500										
M2OC										
REFI										
VOL										
FF										

Key:
= lagged causes only
= contemporaneous causes only
= lagged and contemporaneous causes

Notes: based on the detailed SVAR specification in Appendix B.

Figure 1
Initial Contemporaneous Causal Graph

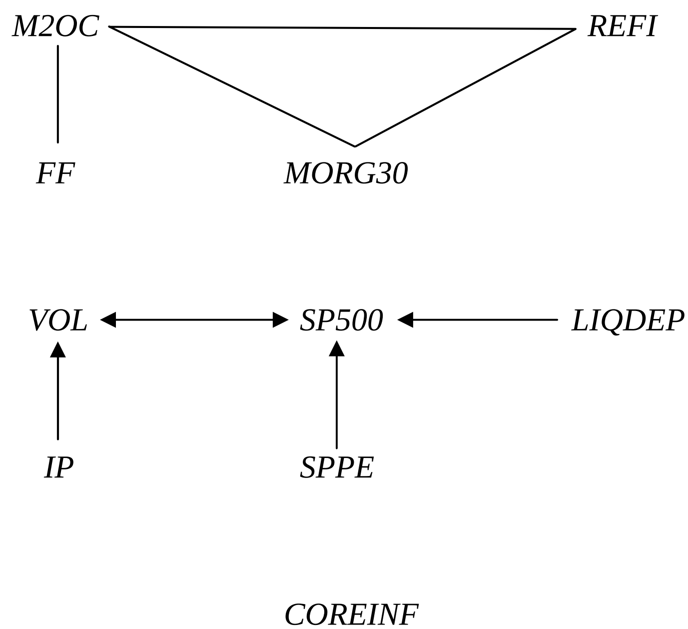


Figure 2
Final Contemporaneous Causal Graph

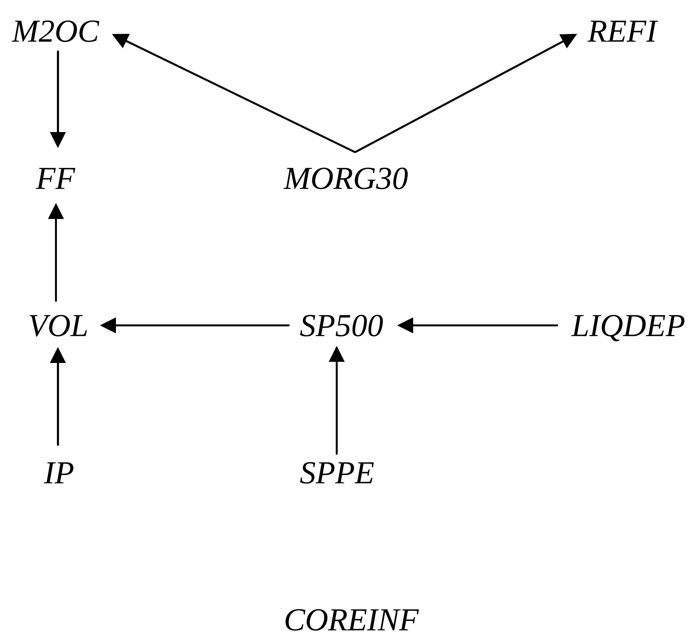
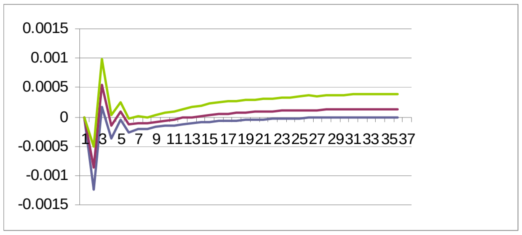
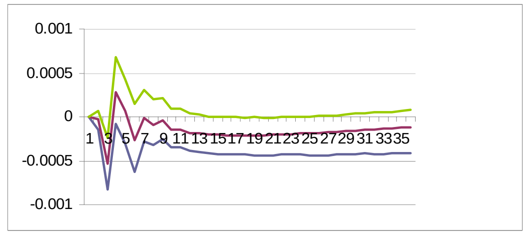


Figure 3
Impulse-response Functions of *LIQDEP* to Shocks to Other Variables

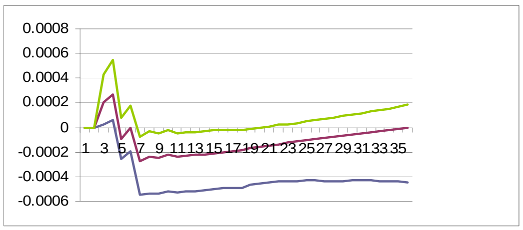
LIQDEP to *FF*



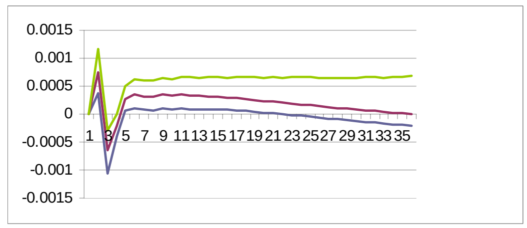
LIQDEP to *VOL*



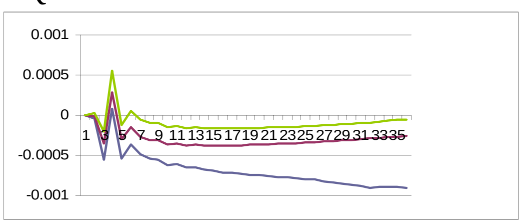
LIQDEP to *COREINF*



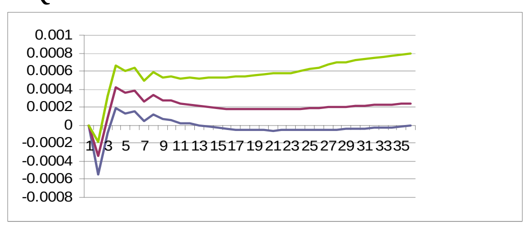
LIQDEP to *SP500*



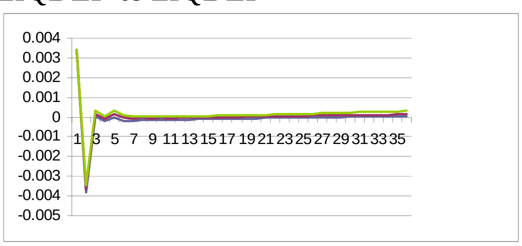
LIQDEP to *IP*



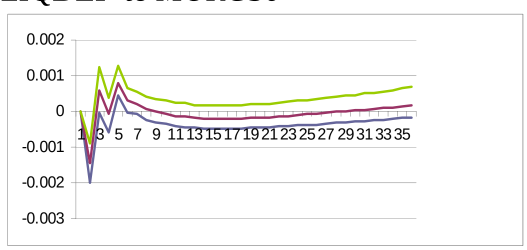
LIQDEP to *M2OC*



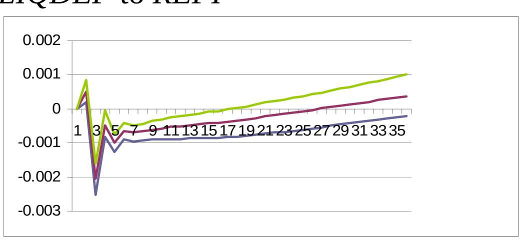
LIQDEP to *LIQDEP*



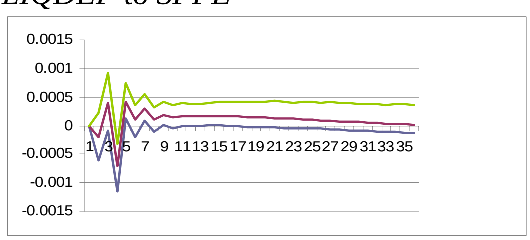
LIQDEP to *MORG30*



LIQDEP to *REFI*



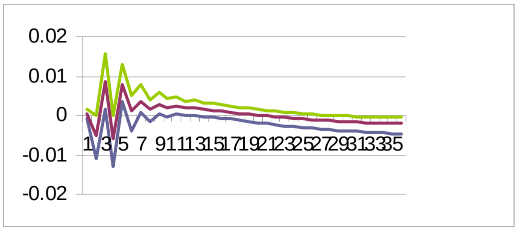
LIQDEP to *SPPE*



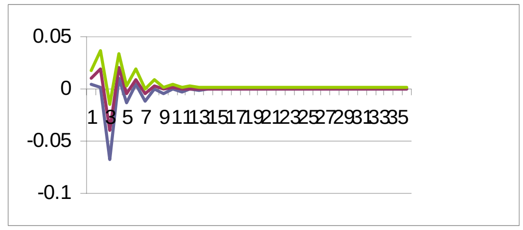
Note: impulse-response functions are shown with ±2 standard-error bands.

Figure 4
Impulse-response Functions of Other Variables to Shocks to *LIQDEP*

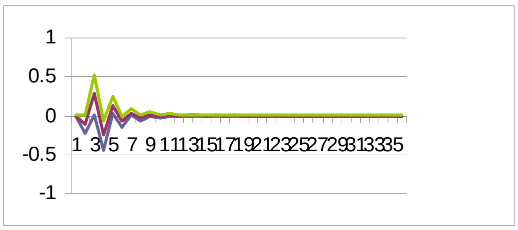
FF to *LIQDEP*



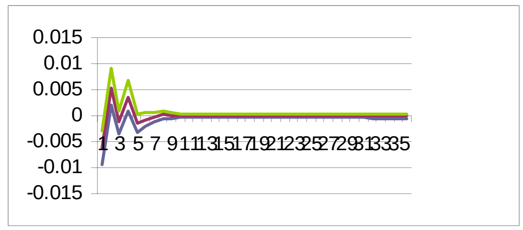
VOL to *LIQDEP*



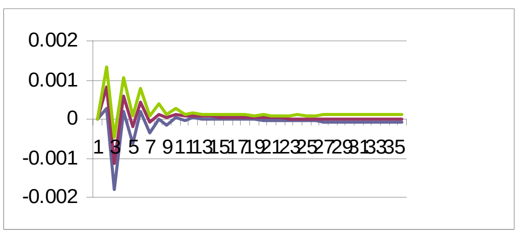
COREINF to *LIQDEP*



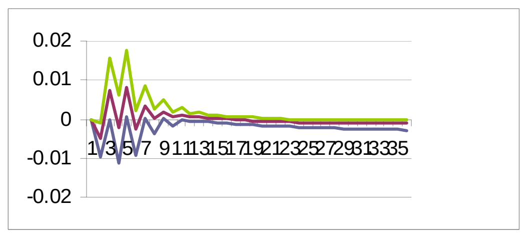
SP500 to *LIQDEP*



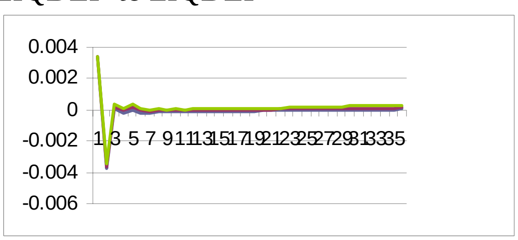
IP to *LIQDEP*



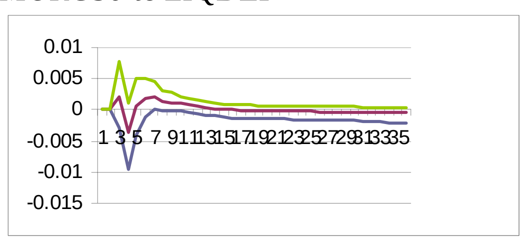
M2OC to *LIQDEP*



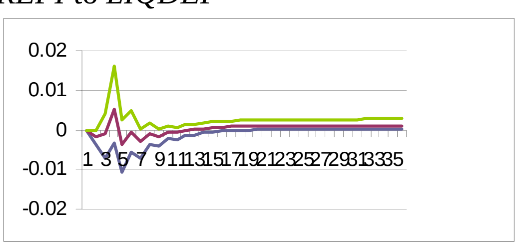
LIQDEP to *LIQDEP*



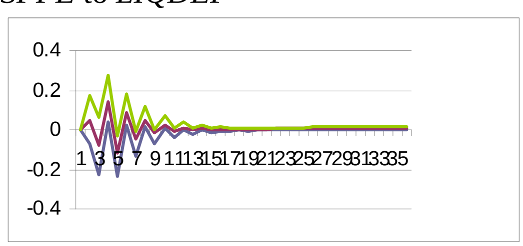
MORG30 to *LIQDEP*



REFI to *LIQDEP*



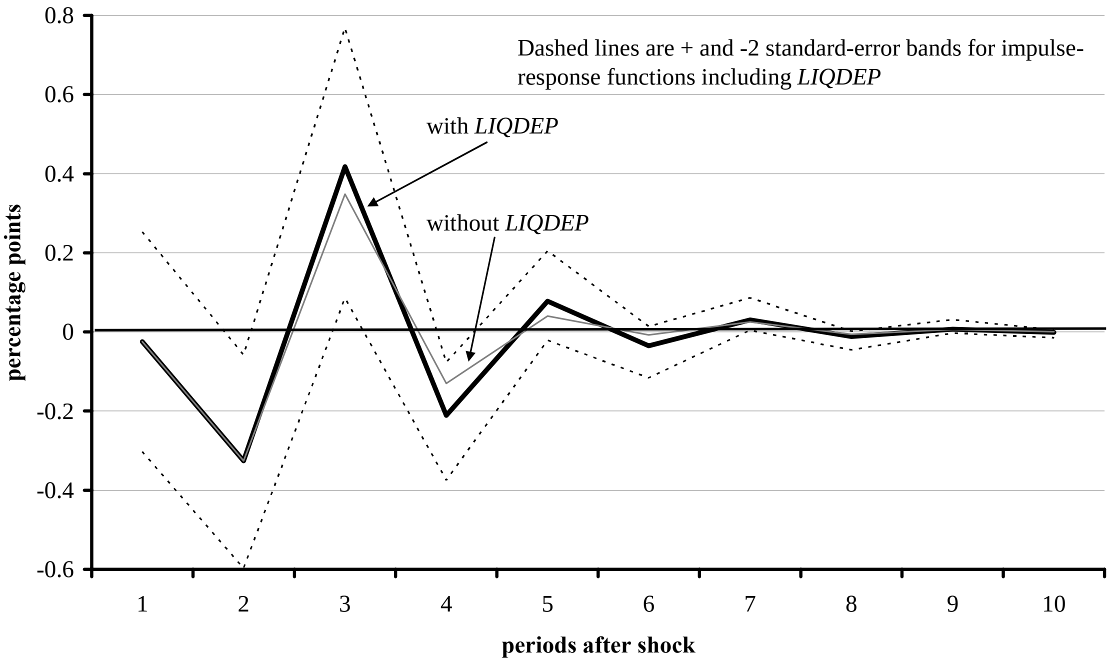
SPPE to *LIQDEP*



Note: impulse-response functions are shown with ±2 standard-error bands.

Figure 5.A
The Importance of *LIQDEP* in the Transmission of Monetary Policy

Impulse Response of *COREINF* to permanent 25-basis-point shock to *FF*



Cumulative Impulse Response of *COREINF* to a 25-basis-point shock to *FF*

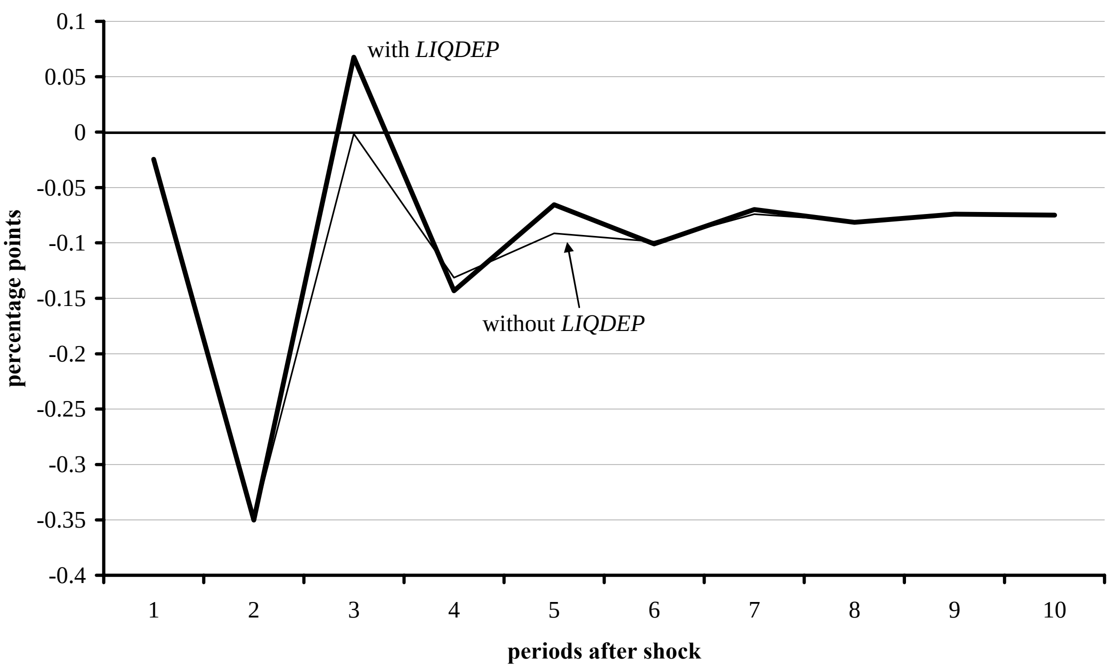
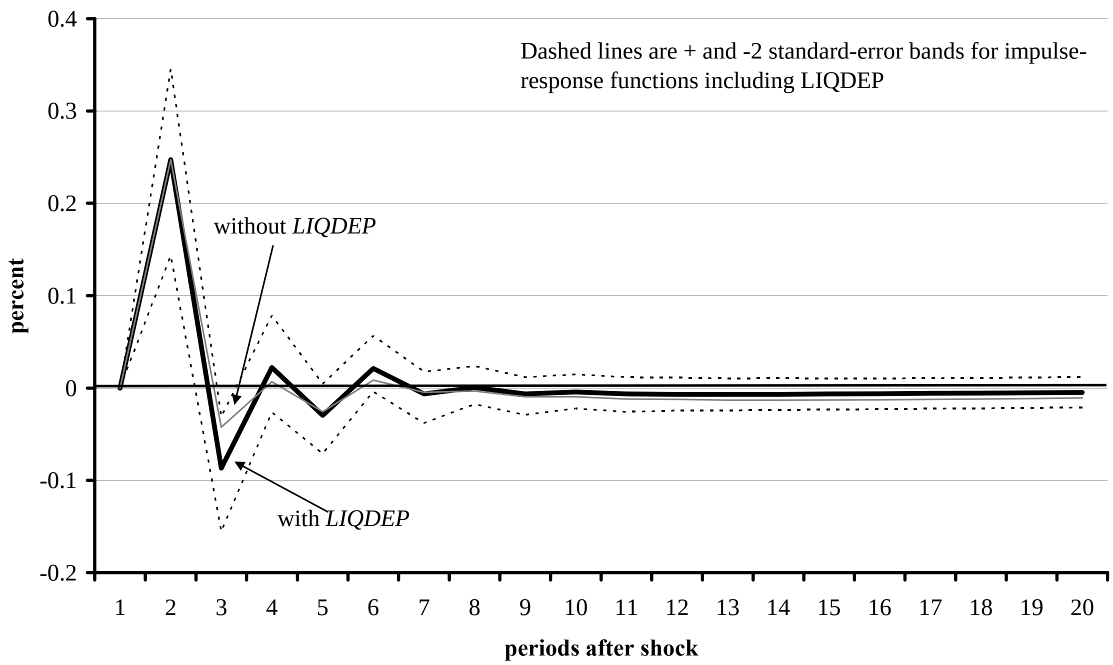


Figure 5.B
The Importance of *LIQDEP* in the Transmission of Monetary Policy

Impulse Response of *IP* to permanent 25-basis-point shock to *FF*



Cumulative Impulse Response of *IP* to a 25-basis-point shock to *FF*