Leverage Cycles in a Mature Asset Class: New Evidence from a Natural Laboratory *

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Abstract

We model leverage cycles in the natural laboratory of a mature asset class, namely US Commercial Real Estate. In this setting we can observe entrepreneurs' asset values as well as debt balance and thus model capital-market yields, as conditioned by market-wide leverage, which indicates debt availability. Using a VAR framework, we examine variance decompositions and impulse-response functions. We show that leverage constitutes the primary driver of innovations in capital-market yields and vice versa. We further find evidence for *flight to quality* as well as knock-on effects that affect low-leverage entrepreneurs in the market.

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1 Introduction

For many years economists have argued that investor leverage plays an important role in the economy. Bernanke and Gertler (1989) describe the effects of leverage on the real business cycle, and also illustrate related capital-market effects through which asset prices fluctuate as a function of debt in the economy. Subsequently, these capital market fluctuations exacerbate the business cycle and generate economically important real effects. The argument is that *entrepreneurs* (i.e. investors) are levered, and a negative shock to their asset values creates debt-capital constraints. This is because lenders become unwilling to lend, due to a lack of collateral. Thus, debt becomes more scarce and expensive, making levered investments less feasible and profitable. This causes a broad decline in the values of those assets for which investors lever up, and through knock-on effects for all asset values. Furthermore, this also causes a decline in asset-market liquidity, which can further depress asset values. As asset values recover, debt availability improves, and the subsequent upturn is magnified by the same mechanism which magnified the previous downturn. This process is referred to as the *financial accelerator* to the macroeconomic cycle (Bernanke, Gertler and Gilchrist (1996)), and much later as a *leverage cycle* (Fostel and Geanakoplos (2008), and Geanakoplos (2010)).

The mechanism described in this research is intuitively appealing. However, modeling this mechanism empirically and determining its economic magnitude as well as its importance for asset markets, has so far proven difficult. We contribute to the literature by constructing the tractable setting of a natural laboratory, in which we can empirically model many of the salient features of the Bernanke-Gertler paradigm and determine their relative importance. The past difficulties in modeling this framework have been due to several factors. First, it is often difficult to observe what Bernanke and Gertler (1989) term *entrepreneurial net worth*, i.e. collateralizable assets on which debt can be secured. In our setting, we can see the value of assets from the perspective of lenders. Next, as Bernanke et al. (1996) point out, there exists an identification problem in modeling leverage cycles empirically, in that theory does not predict a set timing relationship between shocks to credit and shocks to asset prices (and output): a feedback cycle exists, which leads to identification problems. To make things even more difficult, when measuring this phenomenon on an economy-wide basis, it is often difficult to avoid inadvertently capturing output (i.e. cash-flow) effects which may be impossible to separate from pure capital-market (i.e. discount-factor) effects. The latter category should be what drives this type of cycle, since the argument centers around cost- and availability of debt. Our framework addresses these difficulties directly.

Further, in a general equilibrium framework, scarce and expensive credit should draw new suppliers to credit markets to capture the profits from profitable investment opportunities. Regardless of the intensity of new entry, the damage from restricted credit may already be done in terms of depressing asset prices (and output). From the econometrician's standpoint, however, economy-wide empirical estimates might not be able to pinpoint credit effects and their importance in causing a downturn. This is likely part of the reason why Fostel and Geanakoplos (2008) turn to emerging asset classes, as the capital market for these assets is more segmented from other capital markets, and the emergence of new players that re-allocate credit to this market might be more delayed. However, there should not be anything about leverage cycles that makes these phenomena particular to emerging asset classes: we should find these in mature asset classes equally as much. Our natural laboratory consists of a mature and important asset class, in which we are still able to model debt cycles.

The setting we choose for our natural laboratory is the Commercial Real Estate (CRE) market of the United States. This is a large and important asset market: the total value of the asset class was estimated at $11 trillion as of the end of 2009 (Florance, Miller, Peng and Spivey (2010)). At the same time, CRE constitutes a very mature asset class traded in a well-developed market.[1] This setting offers many advantages in modeling leverage cycles. First, we can directly observe both the values of the underlying assets upon which debt is secured (the equivalent of *entrepreneurial net worth*), as well as the outstanding balances of debt secured. Not only this, but we can even observe official appraisals for the underlying assets (i.e. properties held by investors), and can therefore observe lenders' *perception* of *entrepreneurial net worth*, which should be the driver of leverage cycles. Second, we have the advantage of being able to measure asset yields, separate from cash flows in this market. This allows us to model these yields through a Campbell-Shiller VAR (see Shiller (1992)), through which we can directly capture the feedback cycles that are at work here and make attributions of variance, as well as analyze orthogonalized effects. This approach addresses the identification problems that are often found in this type of analysis.[2] Third, the commercial-real-estate debt market is segmented enough from other capital markets to make leverage cycles persist for long enough to capture their dynamics in an empirical estimation.[3]

There are further advantages to the commercial-real-estate setting in modeling leverage cycles. Many commercial-real-estate investors use high amounts of leverage, and any scarcity of debt therefore makes it difficult to invest for those agents. In contrast, some investor groups use little to no debt. We can disentangle two competing hypotheses with regards to these latter investors: either this group could suffer losses due to declining asset values (or liquidity), just like low-leverage entrepreneurs in the Bernanke-Gertler setting. Alternatively, these investors could be able to make profits by being the buyer of last resort for levered investors who need to sell (i.e. a fire sale scenario). Further, in the Bernanke and Gertler (1989) setting, as a downward cycle sets in, a *flight to quality* should occur, meaning that only lower-risk – but also less productive – projects receive debt funding. In our setting, we can distinguish among riskier and less risky investments to test a

[1] For comparison, Wilshire estimates the total market capitalization of US publicly traded equities at $12 trillion at the same point in time.

[2] See, e.g., Bernanke et al. (1996).

[3] Anecdotally, for example, in the resolution to the 2007–2009 financial crisis, new players such as pension funds and private-equity firms entered the market to make commercial-real-estate loans directly. However, there was substantial delay in this new entry, which exacerbated the downturn, since credit supply remained low for an extended time.

lead-lag relationship in deleveraging as the debt cycle sets in.

As mentioned, one of the keys to our natural laboratory is the ability to observe lenders' perceptions of asset values, in comparison to debt balances. Correspondingly, one of our primary variables used in modeling debt cycles becomes industry-wide loan-to-value (LTV) ratio. Due to balance-sheet segmentation on the part of lenders this variable acts as a measure for lenders' perceived debt exposure, and therefore as a measure of debt scarcity, which constitutes the key driver to the debt cycle.[4]

As stated, we model debt cycles by tracking commercial real estate yields (also known as *cap rates*), through the dynamic Gordon-Growth Model setting Campbell-Shiller VAR, the standard methodology for modeling this quantity. We augment this VAR by adding adding state variables of leverage (through LTV) and liquidity (through volume) to model the discount-factor portion of yields.[5] We use data from the National Council of Real Estate Investment Fiduciaries (NCREIF) for our investigation. NCREIF's data allows us to observe valuations, debt balances, cash flows, and transaction volume which will be the key variables of interest in our investigation. These variables are measured throughout a large institutional-quality real estate portfolio encompassing nearly $35,000$ properties, worth close to one trillion US Dollars. NCREIF reports that their portfolio captures the vast majority of institutional capital invested into real estate through private vehicles. The institutional-quality aspect of this portfolio will ensure that we observe data from sophisticated investors, and the portfolio's size ensures that effects we measure are important and relevant to the entire CRE market.

Having estimated our VAR, we examine forecast-error variance decompositions and impulse-response functions. We find that LTV is the single largest driver of innovations in yields; this means that, economically, the debt cycle mechanism is central to the functioning of an asset market. Conversely, we also find that at most time horizons, yield is the most important driver of innovations in LTV, which highlights the feedback mechanism of the debt cycle. We further find that, as predicted by the Bernanke-Gertler model, innovations in volume are importantly driven by yield, as well as LTV. Orthogonal impulse-response functions show that a positive shock in yield (as occurs at the onset of the debt cycle) leads to an initial positive effect in LTV, followed by a subsequent negative effect, exactly as predicted by the model. A positive shock to LTV (as occurs at the onset of the debt cycle) leads to an increase in yield, and decrease in volume.

We next model *flight to quality* by examining the lead-lag relationship of a delevering (which would happen in a downward debt cycle) between riskier and less risky investments, as represented by *Non-Core* versus *Core* markets respectively. We find that *Non-Core* markets lead *Core* markets in delevering, when significant delevering events occur. We then examine the effects of the debt cycle on Open-Ended Diversified Core Equity (ODCE) funds, which, by charter, maintain low degrees of

[4] We address explicitly the character of this segmentation in Section 2.

[5] The capital-market effects of the debt cycle will manifest through yields, since debt scarcity affects investment demand (or feasibility) for a given set of cash flows produced by a financial asset.

leverage. We re-estimate our VAR for these funds and find similar effects for this segment, as we find for the whole sample. This presents evidence that, just like in the Bernanke-Gertler model, low-leverage entrepreneurs also suffer declines in asset values and diminished levels of investment, through knock-on effects in capital markets. The data reject the hypothesis that these low-leverage entrepreneurs profit from fire sales in a downturn; we find that changes in the real estate assets of these funds are negatively related to changes in industry-wide LTV, indicating selling activity in the onset of the downward debt cycle. We lastly present evidence that ODCE-fund investors' requests for redemptions in declining markets are likely behind these funds' inability to invest and profit from fire sales. Thus, as in the Bernanke-Gertler model, low-leverage entrepreneurs are still unable to invest profitably in a downturn.

In the Bernanke-Gertler model, provision of debt depends in part on the collateral value; changing prospects alter the lender's views about collateral. While Fostel and Geanakoplos (2008) model lending contracts to set both the interest rate and the level of collateral, they show that, most of the adjustment in lending contracts takes place on collateral terms rather than interest rate. It should therefore be sufficient to model LTV, which serves as a measure of debt scarcity.

While we do not model this link explicitly, past literature has argued extensively that the Bernanke-Gertler mechanism has important real economic effects. For example, Kiyotaki and Moore (1997) establish this link theoretically, by showing that the effects of asset prices as a function of the leverage cycle then spill over to other sectors and generate (potentially) large fluctuations in output. Analogously to Kiyotaki and Moore (1997), in our framework, lenders have difficulty accelerating loans, and durable assets (the properties) serve the dual purpose of being both production asset and collateral. More broadly, studies that link the Bernanke-Gertler mechanism to real effects abound in the literature: see e.g. Mendoza (2010), Jermann and Quadrini (2012), Christiano, Motto and Rostagno (2014). This mechanism has also been identified as an important channel in banking crises (see e.g. Reinhart and Rogoff (2011), Jiménez, Ongena, Peydró and Saurina (2012)). In many cases these studies assume the effectiveness of the Bernanke-Gertler mechanism and add some salient features of this framework to macroeconomic models. The role of our study, on the other hand, is to test empirically the existence and relative importance of the Bernanke-Gertler mechanism itself.

In commercial real estate, as in Bernanke-Gertler and Fostel-Geanakoplos, debt balances on commercial property are more or less fixed in any period (amortization is essentially completely predictable). Changing collateral values determine LTV, then, and accordingly will determine debt exposure. Since outstanding debt changes very little (and predictably) on existing properties, we have a clean setting in which to assess empirically the predictions from the Bernanke-Gertler/Fostel-Geanakoplos models. This distinguishes our setting from a related literature on the importance of financial intermediaries to asset pricing (see, e.g. Brunnermeier and Pedersen (2009), Adrian and Shin (2013), Gertler and Kiyotaki (2015), He and Krishnamurthy (2013)). In that setting, downturns are related to financial intermediaries' perception that their own leverage (rather than the *entrepreneurs'*) is too high, which makes them stop lending. An important feature of this intermediaries literature is therefore that intermediaries choose to shrink (or grow) their balance sheet (see, e.g. Nagel (2012)). A challenge in the intermediaries literature is to determine who the relevant intermediaries are, as well as to track their balance sheets.[6] The latter is only accomplished through proxies. In our setting we do not have this difficulty: like in the original Bernanke and Gertler (1989) setting, we track *entrepreneurs'* leverage directly. The lenders also track entrepreneurs' balance sheets (using the same information that we observe), and become concerned with their own exposure, as a result of the entrepreneurs' indebtedness. Unlike in the intermediary setting, where the intermediary is essentially the marginal investor, in our setting, as in the original framework, the *entrepreneur* is the marginal investor.

Our setting is also different from papers that examine the impact of housing collateral on the financial accelerator (see, e.g. Iacoviello (2005), or Mertens and Ravn (2011)). There are at least two important differences here: first, housing is primarily a consumption good, albeit with a small investment component; commercial real estate, on the other hand is strictly an investment with no consumption component. This keeps our setting closer to the Bernanke and Gertler (1989) model.[7] Second, in commercial real estate we can observe and model yields, while in housing this is often difficult since prices are observable, but underlying cash flows (which are often only implied) are not.

The rest of the study proceeds as follows. Section 2 presents our natural laboratory and the Bernanke-Gertler model in its context; Section 3 presents methodology and data; Section 4 presents our results; Section 5 concludes.

2 The Natural Laboratory

2.1 The Commercial Real Estate Landscape

Commercial Real Estate (CRE) can be thought of as space in which economic production takes place.[8] As such, commercial real estate is an important production input in the economy. Commercial Real Estate mostly consists of buildings, classified into five major property types: Office, Industrial, Retail, Hotels, and Apartments. The first three sectors serve directly to host economic

[6]For an illustration of this difficulty, which has led to some degree of disagreement, see He, Kelly and Manela (2017) and Adrian, Etula and Muir (2014).

[7]Mian and Sufi (2011) explore the effect of household-debt availability (through increased house prices) on household borrowing decisions. Similarly, a mechanism such as the one described in Mian and Sufi (2014) explores leverage-based shocks to household wealth, as a driver for real economic effects. Somewhat relatedly, Chaney, Sraer and Thesmar (2012) investigates shocks to the value of corporate real estate (measured through local house-price dynamics) on firm investment. Our study, on the other hand, focuses on the leverage cycle's effects on asset prices.

[8]Much of the exposition in this subsection is textbook knowledge and can be found in sources such as Geltner, Miller, Clayton and Eichholtz (2013).

production activities, while the last two support production activities by providing short- and longer-term living space for workers.

The default setup for commercial property is in a landlord-tenant model, in which a financial investor holds the property, and rents it to the firm undertaking the economic production.[9] The profits to investors are directly tied to the economic activity that takes place in the buildings, as this drives rents. The commercial-real-estate landscape thus constitutes a microcosm for a production economy, whose product consists of various types of *space*.

Properties are bought and sold by investors along purely financial decisions, (risk-return tradeoffs) just like any other financial asset that aides economic production. This contrasts strikingly with housing. Housing is primarily a consumption asset, in which purchase decisions are made primarily according to the consumption value of the house (things like kitchen- and bathroom design, proximity to amenities or work, quality of schools, etc.). In housing, financial decision making (along the lines of risk-return tradeoffs) plays only a very minor role.[10] In commercial property on the hand, on the part of the investor (i.e. the landlord), consumption-type amenities only matter to the degree in which they affect the cash flows generated by the properties. The investor (i.e. entrepreneur) derives no consumption value from CRE. Once again, CRE is purely a financial asset.

Commercial properties as financial assets are traded in a large and active private asset market. Compared to, say, common equity, this market is characterized by low liquidity, slow transactions, and high transaction costs. Another key characteristic of commercial property is its tangibility and redeployability. This gives these financial assets a high debt capacity: securing debt on commercial property (through mortgages) is cheap and relatively simple. For this reason, many CRE investors use high amounts of leverage, since positive leverage to an equity holder is easy to achieve in this environment. For this reason availability of debt is key in order to ensure the functioning of this financial market; equity-only transactions are done by only the most conservative investors. This is a reason why CRE is a well-suited natural laboratory to model the Bernanke-Gertler debt cycle empirically.

The CRE investment opportunity set is commonly divided geographically into *gateway*- and *non-gateway* markets. The former category consists of the largest metropolitan areas; the latter consists of metropolitan areas outside this set. This distinction is important for institutional investors, as *gateway* markets are thought to be less risky, in part but not only due to their high level of liquidity.[11] [12] This distinction will become important when modeling *flight to quality* in

[9] Owner-occupancy by firms, while it exists, constitutes the exception, not the rule, and specific rent-vs-buy choices are so far not well understood in the literature.

[10] The vast and long-lived hedonic pricing literature, which attempts to price houses according to each consumption aspect they feature, as well as the hedonic-index literature which highlights the importance of adjusting for consumption characteristics bears witness to the dominance of this way of thinking about housing. This long line of literature dates back to at least Bailey, Muth and Nourse (1963) and Rosen (1974).

[11] Once again, this is textbook knowledge. However, in recent work this distinction is also treated explicitly in Ghent (2018).

[12] For examples of *gateway* and *non-gateway* markets, see Table 1 Panels B and C.

a downturn in the Bernanke-Gertler world. At such times we should see capital moving towards *gateway* markets.

The major institutional investors in CRE equity in the United States consist of REITs (Real-Estate Investment Trusts), and private-equity funds. CRE private-equity funds (on which our data focuses) can be divided into Core Open-Ended funds (termed as Open-ended, Diversified, Core Equity, ODCE, by NCREIF), other Open-Ended funds, Separate Accounts, and Closed-Ended Funds.

Core Open-Ended funds tend to be the most conservative players, in that their purpose is to mimic a nearly passive, broadly diversified portfolio of high-grade commercial real estate (termed "Core" investments); this is the closest structure to an index fund in CRE. In line with their conservative orientation, these funds use little to no debt. The "open-ended" feature of these funds is important to understand. In theory, these funds are like equity mutual funds, in which investors can move in and out (make *contributions* or *redemptions*) at net-asset-value (NAV), whenever they choose. In reality, for any open-ended fund, contributions force the fund to purchase more investment assets, while redemptions force the fund to sell assets. Especially the latter can be problematic in CRE, in that transactions are slow and expensive.[13] In order to protect themselves from quasi bank runs, open-ended CRE funds honor redemptions only on a best-effort basis, with redemption requests being assembled in a *redemption queue*; this is worked down in order, the next time the fund sells assets and has cash to disburse. However, in reality, it is beneficial to a fund's reputation to be able to honor redemptions in a timely fashion, and so the fund holds cash reserves, for this purpose. In our study, ODCE funds will serve to shed additional light on the effects of the debt cycle, in that they are low-leverage players in a market in which the availability of leverage is otherwise extremely important. These funds become the low-leverage entrepreneurs in the Bernanke-Gertler world.

Non-core open-ended funds have a structure similar to the one described above, except that they follow less conservative strategies (which are collectively known as as *core-plus*, *value-added* or *opportunistic*). Separate Accounts consist of the CRE holdings of large pension funds or endowments, who essentially set up a private fund exclusive to them, with a large fund management company. These entities pursue a variety of strategies, and employ a variety of levels of leverage. Lastly, Closed-Ended Funds are set up in the classic private-equity model, as partnerships or limited-liability companies, with a pre-defined life time, and virtually no secondary market. These funds tend to pursue the most aggressive strategies. As with any aggressive investment fund, these funds can be very susceptible to market fluctuations.

CRE debt is generally held by three major types of entities: Banks, Commercial Mortgage-Backed Securities (CMBS), and, more recently, directly by large institutional investors such as private-equity funds, pension funds, or life insurance companies. Banks and private-equity funds

[13] For example, a transaction time of six to nine months to sell a major office building is considered normal.

hold loans directly on their balance sheets. CMBS are vehicles for securitization of mortgages (similar in setup to Residential Mortgage-Backed Securities, although without any implicit guarantees against default), through which mortgages are pooled, and their cash flows sold off through bonds of various seniority.

In most cases, the capital market for CRE debt is segmented from other debt markets, at least in the short term. For a bank, for example, there tend to be maximum exposures to commercial real estate risk that an institution is willing to- or allowed to- take. In other words, bank balance sheets are segmented.[14] Internally, banks regulate CRE lending as a function of debt-to-asset values, or overall effective Loan-to-Value (LTV). Senior managers treat LTV as an instrument to managing bank lending, lowering LTV requirements when they wish to make fewer (or smaller) loans, and raising LTV when the bank's appetite for risk (or earnings) is elevated. In a declining market, when effective LTVs rise (the onset of the debt cycle), the state of the rest of the bank's balance sheet tends to be largely irrelevant: the bank will not be able to make new CRE loans, causing scarcity of debt in the market, as in the Bernanke-Gertler world. In theory, many CRE loans also contain provisions that would allow the lender to accelerate the loan and force the sale of a property, if an LTV threshold is crossed. In practice, however, if a loan is performing, this is often not enforced, as an immediate sale would make the lender worse off, by realizing the capital loss. In any case, though, the lender will not make new CRE loans, causing debt scarcity. Ultimately, the overall state of the bank's balance sheet is not the driving factor for CRE debt availability. Rather, it is the degree of leverage present in the CRE industry.

A similar story can be told for CMBS. When effective LTVs on existing mortgages spike, this devalues the bonds secured by the mortgages in a particular deal. Subsequently, it will not be possible to raise new CMBS deals, and so this source of debt capital will dry out, making debt scarce in this financial market. Therefore, the measure of market-wide Loan-to-Value (LTV) ratio should be a good proxy for what Bernanke and Gertler term the *condition of the entrepreneur's balance sheet* which drives the effects associated with the leverage cycle.[15] We therefore use this measure throughout our study.[16]

The exception to the debt-market segmentation might be private-equity funds or life insurance companies, which make loans directly, as part of a larger investment portfolio. Incidentally, this form of lending was virtually born in the recovery from the last financial crisis, in which these funds entered the market as new players to capture the high yields available in a debt market that was otherwise in distress. Nevertheless, direct lending by private equity funds remains small enough

[14]Evidence for this can be found, for example, in Popov and Udell (2012): the effects of this balance-sheet segmentation drive the effects studied there. US banking regulators have also implemented a requirement in the 2014 Basel III banking rules requiring higher capital reserves for bank loans against what is called High Volatility Commercial Real Estate (HVCRE). These exist regardless of the state of the rest of the institution's balance sheet.

[15]By charter, Government-Sponsored Agencies (such as Fannie Mae and Freddie Mac) are also allowed to make CRE loans, but only on multi-family properties. Even with these entities, however, LTV constraints are severe, in that maximum LTV for loans they are allowed to purchase is explicitly limited in their charter.

[16]CRE debt is largely property-specific; private-equity funds as an entity do not take on debt separately.

that the effects associated with the Bernanke-Gertler debt cycle remain in place.[17]

2.2 The Economics of the Leverage Cycle

We now describe the essential features of the leverage cycle as it unfolds in our natural laboratory. As in Bernanke and Gertler (1989), the balance sheets of entrepreneurs are central to the story. In the case of Commercial Real Estate, the entrepreneurs are the owners of the properties. Each property can be seen as an investment project undertaken by these entrepreneurs. The *condition of the entrepreneurs' balance sheet* is then nothing but the degree of indebtedness of each property, as measured by LTV. This is because, from the property owner's standpoint, there is no other source of debt, than a mortgage secured by the property, since these funds do not take fund-level debt. From the lender's standpoint, as well, nothing else is relevant, due to the debt market segmentation discussed above. LTV is all there is in this setting, and we can measure it.

Note that in this world the properties are not only the projects that generate cash flows for the entrepreneurs, but they also act as collateral to the lenders.[18] As in the Bernanke-Gertler model, the debt cycle is set in motion by a negative shock to collateral values, or, in this case, property prices. As in the Bernanke-Gertler world, this is, initially, exogenous. The immediate effect of this shock is to raise LTVs (since debt balances are unchanged and property values have decreased). This raises lenders' perceived debt exposure, which makes lenders less willing to make loans. This, in turn, makes debt more scarce, which manifests through tightened lending standards, especially in terms of LTV requirements. As in the Bernanke-Gertler framework, this makes it more difficult for entrepreneurs to invest (i.e. for potential investors to buy commercial property) since they cannot obtain leverage.[19] This reduces demand for properties by investors, further depressing prices; at the same time liquidity is reduced, which again reduces asset prices. This exacerbates the situation, by generating further upward pressure on LTVs.

In the Bernanke-Gertler model, as the downturn continues, we see a *flight to quality*: namely, only lower-risk but also less productive projects are undertaken. In Commercial Real Estate, this should manifest through capital fleeing to *core* markets (the largest geographic areas), with secondary markets therefore leading the downturn. We can measure this in our setting.

Once the market turns around, as in the Bernanke-Gertler model, we should see the opposite set of effects, which accelerate the upturn. As property values recover, LTVs are lowered, lenders become more willing to lend, and investors obtain leverage more easily. This raises investment demand and liquidity, and further raises asset prices, raising LTVs. As the cycle continues upward,

[17] For example, the National Association of Realtors shows that for 2016, CRE loans by "U.S. Chartered Depository Institutions" accounted for slightly more than half of CRE loans issued, with CMBS and Government Agencies accounting for 10% and 18% respectively. In comparison to this, life insurance companies made 11% of loans.

[18] This feature is in line, for example, with the representation of Kiyotaki and Moore (1997).

[19] As mentioned above, there could be some lenders which accelerate loans and force distressed sales of property at this time, in addition to being unwilling to lend. While this is likely a fairly isolated occurrence, any such occurrences would put further downward pressure on property prices and exacerbate the downward cycle.

lending standards will also be loosened, making debt even more available, including for riskier projects, and higher leverage.

For the entrepreneurs (i.e. property owners) the leverage cycle plays out largely along the lines of investment demand (or feasibility). From this, it follows that, in order to understand the capital market effects in the property market, the relevant quantity to observe is yield, and not overall price. Yield measures (the inverse of) investment amount per unit of cash flow. Given a set of cash flows produced by a property, the investor/entrepreneur will determine the amount of money she is willing to pay for this asset. The aggregate of these marginal buying decisions constitutes the outcome in the capital market. Once the downward cycle sets in and debt becomes unavailable, this lowers the returns to equity holders and makes CRE less attractive as an investment. Therefore, the investor is willing to pay less for the same property, producing the same cash flows. Price has declined, but fundamentally this was due to an expansion in the yield applied by the investor.

The other type of price decline one could see in the CRE market would be due to a decrease in cash flow (i.e. rental payments). In fact, in real estate we distinguish between space markets, which generate rental payments, and capital markets, which apply yields to the stream of rental cash flows to then determine asset prices. A price decline that stems from the space market (and therefore from cash flows) would have to be linked to a reduction in profitability of the economic production that takes place inside the property. The availability of commercial mortgages should have no direct economic linkage to production activity and therefore rent payments. Thus, for the purposes of modeling the Bernanke-Gertler world, we are only interested in price changes that are caused by changes in yield; thus we are ultimately interested in yield itself. In an idealized laboratory environment the onset of the debt cycle could take place with no movement in rental cash flows at all. In reality, however, rental payments do fluctuate: modeling yield directly controls for this.[20]

While the initial price shock that sets the debt cycle in motion could come from either yields or cash flows (or a combination), the feedback cycle back from LTV to the capital market would go to yields. For empirical tractability, it would be difficult to simultaneously model both yields and total prices. If we modeled only prices, we could inadvertently catch feedback effects that are unrelated to the capital-market portion of the debt cycle (i.e. output effects). By modeling only yields, we therefore impose a tighter standard on our study, in that we may be understating true effects. This is the conservative choice.

How do debt cycle effects finally translate into space markets (and therefore cash flows)? This only happens deeply into a cycle when depressed asset prices cause a lack of investment, and therefore a lack of availability of space for economic production. All else equal, at this point the

[20] As stated before, a common problem in attempting to model the debt cycle is, in fact that debt-cycle phenomena then feed through to economic output, and the nature of the effects involved becomes muddled. By being able to cleanly model yields, we overcome this problem.

scarcity of space actually causes an *increase* in rents.[21] This would then actually begin to cause the market turnaround, as the increase in rents would raise asset prices.[22] We do not model this part of the cycle explicitly, but leave this to further research.

In our setting we also have a set of no- or low-leverage investors, in the form of our ODCE funds. In the Bernanke-Gertler framework, these investors would eventually also suffer losses, due to knock-on effects of the capital market downturn which ultimately extends to all asset prices in some degree. A competing hypothesis, however, would be that these funds, due to the absence of their need for leverage, act as buyers of last resort to sellers of distressed assets and profit from the purchase of assets at fire-sale prices. We will be able to assess the effect of the leverage cycle on these players as well.

We thus have an ideal natural laboratory in which to model the debt cycle, in that we can cleanly measure the state of entrepreneurs' balance sheets, and can cleanly model yields, the variable of interest to understand capital-market effects.

3 Empirical Methodology and Data

3.1 Empirical Methodology

The Bernanke-Gertler model describes a process by which declining collateral values cause debt scarcity, which has adverse effects on prices in the entire capital market. In this process, the cash flows underlying the assets remain initially unaltered. Therefore, the mechanism manifests as a change in the yields applied to cash flows by the market. For this reason, our empirical methodology centers on modeling the cash-flow yields applied by the capital market, rather than asset prices as a whole. The ability to do so constitutes one of the great advantages of our natural laboratory.

In financial asset pricing, one of the most suitable methodological frameworks in which to empirically model capital-market yields is the Campbell-Shiller Vector Autoregression (VAR) (see Shiller (1992)). This framework constitutes an empirical characterization of the asset market's price formation process, and therefore allows a decomposition of the drivers of variance in this market. Further, the Bernanke-Gertler model describes a feedback cycle, in which declining asset prices affect leverage, and declining leverage affects asset pricing. A VAR is an appropriate empirical tool for such feedback cycles, and thus using this methodology helps us overcome the identification problem described in Bernanke et al. (1996).

The Campbell-Shiller VAR characterizes a Dynamic Gordon Growth Model. Broadly, we can write the yield model as

[21] The prevailing modeling framework here is DiPasquale and Wheaton (1992).

[22] In practice, capital-market downturns are often accompanied by real economic downturns, which decrease the demand for space, since production is reduced. In that case, the recovery would be delayed until production recovers.

$$\delta_t = \sum_{j=1}^{\infty} \rho^j E_t \left[r_{t+j} - \Delta d_{t+j} \right] + C \tag{1}$$

This can be estimated as a VAR system with an equation for each of property yield (δ), the risk-free interest rate (r), and cash-flow growth (Δd) as follows (where all enter in natural logs):

$$\begin{bmatrix} \delta_t \\ r_t \\ \Delta d_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \delta_{t-1} \\ r_{t-1} \\ \Delta d_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix} \tag{2}$$

Campbell and Shiller test a null of constant expected returns, and so they omit discount-factor variables. However, debt effects in the Bernanke and Gertler world should drive discount factors in asset markets. Therefore, we add corresponding discount factor variables to the Campbell-Shiller model. Since the model is specified in log terms, these enter additively, and can thus augment the VAR as additional state variables.

The core element of the Bernanke-Gertler framework in a commercial real estate setting is that changes in property value (i.e. change in yield, in this case) are a function of changes in *Entrepreneurial net worth*, i.e. the asset value relative to debt balances, or loan-to-value (LTV). [23] In the Bernanke-Gertler framework, once debt becomes scarce, liquidity of the market is adversely affected, which in turn further depresses asset prices. We measure liquidity through transaction volume. We thus augment the Campbell-Shiller VAR by adding as discount-factor variables aggregate LTV, as well as volume, both in logs.

If our asset market is driven by the Bernanke-Gertler mechanism, our model should capture the following relationships. Yields should drive LTV. Upon an initial yield shock, this effect is initially mechanical, since with constant cash flow, a change in the building yield changes value and therefore LTV. However, in addition to this, we should see a tightening of lending standards once the downward debt cycle sets in, which lowers LTVs beyond their mechanical variation due to changing yields. LTV, in turn, should drive yield and volume, since reduced debt availability depresses asset markets. This completes the Bernanke-Gertler feedback cycle. Lastly, volume should drive yields, as market liquidity determines prices to some extent.

The full VAR model then becomes:

$$[LTV_t, vol_t, \delta_t, r_t, \Delta d_t]' \tag{3}$$

[23] As stated before, while Fostel and Geanakoplos (2008) allow collateral values and interest rate to be jointly determined, they still find that collateral requirements are the primary driver for debt-contract availability.

In the above notation, we construct δ_t (yield), conceptually, as property net operating income (NOI) over transaction price, and LTV as debt balance outstanding, over appraised property value.[24] All variables are aggregated across the NCREIF portfolio as value-weighted averages or sums, respectively.

Once we estimate the VAR, standard forecast-error variance decompositions and impulse response functions will reveal the relative contributions of leverage changes on yields. These measures, because they are orthogonalized, should generate a clear interpretation of LTV-yield dynamics since they are based on a well-recognized solution to the identification problem (see Bernanke, Gertler, and Gilchrist for an extensive discussion of identification issues). This will allow us to test this framework empirically, as well as determine the relative importance of the debt-cycle mechanism to an asset market.

3.2 Data

The NCREIF (National Council of Real Estate Investment Fiduciaries) data is the foundation of our empirical work. This is a vast ($500 billion) database of US property holdings, and covers the majority of privately-held institutional-grade commercial real estate in the United States. The primary entities reporting data to NCREIF are Commingled Real Estate Funds (CREFs); they report trade and return data to NCREIF under a strict non-disclosure agreement and with a long-term commitment. These entities report to NCREIF data on their property-level holdings and transactions. While membership in NCREIF (and thus reporting of transactions to NCREIF) is voluntary, inclusion in NCREIF's database is considered desirable and prestigious on the part of private managers. NCREIF's stated policy is to report data only on high-grade institutional-quality commercial real estate. Inclusion of one's properties in NCREIF's database and indices is viewed as confirming a level of quality for the included investor. As a result, most eligible managers choose to become members of NCREIF, and thus subject themselves to quarterly reporting of transactions and property financial information. NCREIF membership constitutes a long-term contract and commitment, and once included, it is not possible for an investor to report performance only in certain quarters and not in others; the investor is contractually obligated to report all transactions going forward. Data reported by NCREIF members to NCREIF is protected by a strict non-disclosure agreement.[25] Thus, manipulating performance numbers is viewed as ineffective. The primary purpose for which NCREIF uses the data reported to it is for construction of the National Property Index (NPI), the de-facto standard commercial-property index series in the United States.

The NCREIF individual property database is made up exclusively of operating properties acquired (at least in part) on behalf of tax-exempt institutions (mostly pension funds) and held in a fiduciary environment. To meet the operating property requirement, the property must exist and

[24] See Subsection 3.2 for more specifics on how these are computed.

[25] As academic researchers, we are given access to NCREIF's raw data under the same non-disclosure agreement.

be at least 60% leased.[26] Only operating apartment, hotel, industrial, office and retail properties are included (although self-storage has been added to the property database recently). Importantly, the accounting of the property must be performed using market value accounting methods. All existing properties that are purchased, regardless of current occupancy, are defined as operating properties. For a newly-developed property, operating is defined as reaching 60% occupancy or having been available for occupancy for a year from its certificate of occupancy.

As of the first quarter of 2018, the NPI reflects investment performance for 7,553 commercial properties, totaling $567 billion of market value. Figure 1 displays the evolution of the NCREIF portfolio value since the inception of the database in 1978.[27] The market value composition by property type is about 37% office, 24% apartment, 23% retail, 15% industrial and 1% hotel properties. The NCREIF property database also has a large geographic diversification with properties in over 100 Core-Based Statistical Areas (CBSAs). The database is free of survivorship bias.

The NCREIF database provides, among other things, the following data that is particularly essential to our empirical work: listings of properties held in each manager's portfolio; transaction dates and prices for properties; quarterly income (NOI); regular property appraisals; running outstanding-debt balances for loans secured on properties. We aggregate all data in each quarter on a value-weighted basis, either directly, or by use of an index (see below). The last two variables are the constituting elements of our LTV variable.

Due to the scarcity of transactions in commercial real estate, performance evaluation in this industry frequently relies on the use of appraisals. It is well documented in the Commercial Real Estate literature (see e.g. Geltner (1991), Clayton, Geltner and Hamilton (2001)) that appraisals suffer from a bias that results in a set of values that are smoothed across a time series. This smoothing, while leaving long-term first moments approximately intact, results in understatement of volatility, and therefore makes performance evaluation difficult. The NPI is known to suffer from this problem.

For our study, this has the following implications: for the construction of our LTV variable, this is actually a desirable feature. This is because in the Bernanke-Gertler world, *perceived* debt exposure by lenders and not true debt exposure by lenders matters. Given that lenders require appraisals (due to the lack of trading and therefore prices for the property on which a loan is secured), they use these appraisals as their exclusive source for determining their exposure. Given that this same appraisal is reported to NCREIF, we are observing exactly the right quantity. In fact, if we somehow were able to infer a "true" value for the property (which lenders were not able to observe) and used this for the construction of our LTV variable we would be mismeasuring

[26] Development projects might exist in the property database, but they only enter the NCREIF Price Index (NPI) once they reach 60% occupancy or have had a certificate of occupancy (CO) for a year. If a property has been recently purchased with a "redevelopment" strategy and the property is undergoing substantial expansion, re-tenanting, rehabilitation or remodeling, the property is defined as operating when occupancy reaches 60%.

[27] Note that this growth is both due to increase in coverage of the data, as well as organic growth of property values, and it should not be relevant to our empirical setup to distinguish among these two at this point.

lenders' perceived exposure, and therefore debt scarcity.

For the computation of yields, appraised values are more problematic, in that appraised values essentially show a moving average of the unobservable true values, and we would therefore observe a moving average of yields. For this reason, to compute yields in our full-sample analysis, we use NCREIF's Transaction-Based Index (TBI), NCREIF's repeat-sales index. For this index, NCREIF offers a price-appreciation series and a total-return series. The latter is a sum of price appreciation and income returns earned by the portfolio. The yield becomes:

$$y_t \quad = \quad (tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} \tag{4}$$

where *tot.ret* is the total return to the TBI and *app.ret* is the price-appreciation return.[28]

As stated, the NCREIF TBI is a repeat-sales index. Such a methodology requires a sufficiently large number of transactions. For this reason, NCREIF only offers this index at the very highest levels of aggregation (total, disaggregated into four property types, and disaggregated into four geographic regions). These are the levels of aggregation which feature enough transactions for the computation of a transaction-based index to be feasible. In our study, to test how low-leverage players are affected, we use only data from ODCE funds. Regrettably, for this set of funds there are insufficient transactions to make the computation of a repeat-sales index feasible. Therefore, for this part of our study we have no choice but to rely on appraisal-based values when transactions are unavailable.

While our results for ODCE funds might be affected by the limitations of this data, several mitigating factors arise in the context of our study. The appraisal-smoothing literature in commercial real estate agrees that smoothing introduces excess autocorrelation in prices, especially at a one-quarter and four-quarter lag (due to effects called *stale appraisals* and *appraisal anchoring*). Given that in our study we use the yield data in a VAR that contains at least four lags (and for the majority of our study eight lags), the lag structure of the VAR should control for this excess autocorrelation. Further, in a forecast-error variance decomposition, an excess autocorrelation in a VAR variable should bias results against finding cross-variable dependencies; therefore the dependencies we do show are actually a lower bound for true cross-variable dependency between the state variables in our system. Despite these mitigating factors, of course we do use transaction-based yields where these are available.

Our sample period extends from the first quarter of 1982 through the end of 2017. While there is a clear, upward trend in building prices over that period, our VAR methods are ideal for controlling any trends in the underlying data.

Since leverage is at the center of our project, it is essential to understand and accommodate the different leverage strategies used by funds that report to NCREIF. The use of leverage seems to vary quite substantially in the sample. As stated above, ODCE funds are quite often equity-only

[28] For derivation, see appendix.

in the early part of the sample, and even later use very little leverage. REITs (of which there are few in the sample, though) have highest leverage (around 60% LTV). There is considerable variety in the leverage of the property owners that lie in between these two extremes. The variety in the sample contributes power to the empirical analysis.[29]

We now describe further the institutional landscape of ODCE funds, which will serve as our low-leverage entrepreneurs. The ODCE universe consists of 36 funds that pursue a diversified core investment strategy, primarily through private equity real estate investing; the data begins in the later 1970's. The specific NCREIF guidelines require that at least 80% of the market value of net assets must be invested in real estate with no more than 20% invested in cash or equivalents (these funds do not have stock or bond holdings, for example). In addition, at least 95% of market value of real estate net assets must be invested in US markets with at least 80% of market value of real estate net assets invested in office, industrial, apartment and retail property types. These funds do **not** function primarily as development funds; instead, at least 80% of market value of real estate net assets must be invested in operating properties, and the remainder may be invested in, but not limited to, (pre)development/redevelopment or initial leasing/lease-up cycles.[30] Finally, and very importantly for our purposes, the fund may use no more than 40% leverage. NCREIF defines leverage as "the ratio of total debt, grossed-up for ownership share of off-balance sheet debt, to the fund's total assets, also which are grossed-up for such off-balance sheet debt." These funds typically use substantially less than this upper limit, and some funds have zero leverage.

By contrast, there are many other funds in the NCREIF universe that make extensive use of leverage, and pursue a variety of investing strategies that do not meet the diversification requirements associated with the ODCE funds. These others funds typically pursue value-added/opportunistic strategies that involve creation of new buildings (development) or redevelopment of existing buildings. By comparison with the ODCE funds, funds with these investment strategies generally have higher average leverage, more non-operating properties (i.e., development and re-development assets), higher vacancy levels, and use fund structures with fixed lives and no early redemptions of invested capital. These funds will also include a broader array of property types in the underlying investments.

Panel A of Table 1 provides a first look at variations in LTV in our sample. Mean LTV is a bit under 20%, but conditional on there being leverage on a property, mean LTV is a bit over 43%. This conditional sample is the one we use to compute our industry-wide LTV measure, which we use as a state variable in the VAR. This choice should be warranted, in that the variable that drives the Bernanke-Gertler debt cycle is each individual entrepreneur's balance sheet, not the collective

[29]There is a substantial decline in leverage after 2010 which may reflect, in part, the impact of Fed policy. The orthogonalization embedded in our variance decompositions and IRFs accounts for Fed policy. That is, our leverage cycle results hold in spite of (not because of) Fed policy.

[30]The ODCE designation requires that funds meet a diversification requirement wherein the largest property type/region combination may be no more than 65% ($\pm$ for market forces) of the market value of the fund's real estate net assets.

leverage in the economy. LTV constraints are reached on an individual property level, since each property serves as the only collateral to its own loan.

As we noted earlier, the LTV of ODCE funds is quite low, only 12% on average (median below 10%); the third quartile value is a bit under 21% which is substantially lower than the first quartile LTV for LTV conditional on debt being secured on a property.

4 Results

4.1 Variance Decomposition

To assess the evidence for the leverage cycle, we rely primarily on variance decomposition and impulse response function methods. The variance decomposition will indicate the impact on forecast error variance of each variable in the VAR as a function of exogenous shocks to the other variables. Since the timing of the leverage cycle is not known, the variance decomposition functions can also help to characterize the horizons at which different variables have a major (or minor) impact. We use eight lags for the full-sample VAR. The impulse-response functions then show the direction in which this variance manifests.

Figure 2 graphically shows the forecast error variance decomposition for the log of the property yield and Table 2, Panel A, shows this numerically. By examining yield, we establish the relative economic importance of the Bernanke-Gertler mechanism to the functioning of the asset market.

As both the diagram and the table clearly show, shocks to the yield have a very large own effect (i.e. persistence is large). After that, however, LTV shocks have the largest impact on log yields, beginning after two quarters and continuing through the highest of the forecast horizon periods, explaining up to 17% of variation. This quantifies the economic magnitude (and therefore importance) of the Bernanke-Gertler mechanism to this asset market: leverage constitutes the single largest driver of yields, aside from the yield's own persistence. This means that LTV is the primary driver of *innovations* in the yield. In the methodology of the Campbell-Shiller VAR, LTV constitutes an important driver of the discount factor in the market. Shocks to the other state variables appear to matter at longer horizons: the risk-free rate begins to have more noticeable effects after three years, and around five years reaches but does not exceed the magnitude of the effect of LTV, reaching a maximum of 15% of variation. The recognition that the risk-free rate is an important driver of yields in an asset market should not come as a surprise. Conversely, however, it helps further put the magnitude of the effect of LTV into perspective: the impact of LTV on yields is larger than that of the risk-free rate. Income growth (the log-difference in NOI) has very modest effects (3% to 5%) after two years, and volume only matters after five years, steadily increasing in impact from about 1% of variation to almost 6% for the longest forecast period.

We next investigate the evolution of LTV. As Figure 3 and Panel B of Table 2 makes clear, this variable, too, is highly persistent, with own variation accounting for the largest portion of variance.

However, here, too, we find that yield is the largest outside driver of variance in LTV, at least at short and long horizons. Once again, over the short- and long term, yield is the largest driver of innovations in LTV. In the short term, yield explains 5% to 7% of variance, while at long horizons it explains as much as 14%. This importance of yield in driving LTVs constitutes the feedback side of the Bernanke-Gertler mechanism. Recall that the impact of yields on LTVs should be twofold: first a shock on yields raises LTVs mechanically. Later, once yields keep rising (i.e. the market decline deepens), LTVs are lowered due to a tightening of lending standards. These results are consistent with that story. In the medium term (6 to 12 quarters) the risk-free rate becomes the most important outside driver of LTVs, accounting for 5% to 8% of variation, with yield, however, a close second, only accounting for 3% to 5%. Volume becomes relatively important at long horizons, accounting for as much as 6% to 8% at 20 to 24 quarters. At most forecast periods, cash flow growth accounts for about 1% to 2% of variation.

As the discussion in Section 3.1 makes clear, variations in LTV and yields are likely entwined with changes in the volume of building transactions, and so we also examine the forecast-error variance decomposition for this state variable. Figure 4 and Table 2, Panel C, show these results. Like the other state variables, volume is highly persistent, though at longer horizons much less so, than the other two variables we have examined. In terms of outside drivers, property yield, LTV, and the risk-free rate have approximately equal impacts for the first six quarters, explaining about 5% to 9% of variation each. After that, the impact of property yield increases substantially, making this the primary outside driver of volume, accounting for first 14% of variation at 7 quarters, rising to as much as 32% above 20 quarters. This is consistent with the Bernanke-Gertler mechanism, in that the overall state of the capital market should drive liquidity as the debt cycle takes its course (in both directions). However, there could be yield dynamics due to other factors than leverage which could be driving yields. This decomposition cannot tell us, what type of effect is at play. However, the continued presence of LTV as at least a small driver of variance in volume (5% to 8% of variation throughout) does suggest that, at least in part, the debt cycle mechanism has an impact on liquidity in the asset market.[31] The impact of the risk-free rate increases slightly at longer horizons, explaining up to 16% of volatility in yields. The impact of cash flow growth remains small throughout, at 1% to 2%.

These results thus provide evidence for the presence of the Bernanke-Gertler mechanism in this asset market, and for its economic importance. LTV constitutes the most important driver of innovations in yield, and at many horizons the opposite is also true.

4.2 Impulse Response Functions

We now examine the impulse-response functions from the full-sample VAR. These are presented in figures 5-10. In each figure we plot the value of the impulse-response, as well as 90% confidence

[31] Orthogonalized impulse-response functions (which we present next) will be able to shed more light on this issue.

bands, constructed using a bootstrap with 5000 iterations. We track impulse responses to 24 quarters.

We begin by examining the impulse response of LTV to a shock in yield. This is shown in Figure 5. The plot shows a marginal response that is initially positive and increasing for about four quarters, before decreasing and reverting back to zero after about seven quarters. Subsequently the response becomes negative and keeps decreasing, with a trough around 13 quarters and a reversion back to zero. Confidence bands, while wide, do indicate a significantly positive marginal response at the beginning, and a significantly negative marginal response later on.

This impulse response is exactly what the Bernanke-Gertler model would predict, as the downward debt cycle is set in motion. There is an exogenous positive shock to yields (which we are simulating here), which immediately makes LTVs rise, mechanically (since debt balances are constant but asset values have declined). Subsequently as the market downturn continues, lending standards are tightened, and LTVs are subsequently lowered, which makes debt even more scarce. A time horizon of up to three years for tightened lending standards to actually manifest in industry-wide LTVs seems plausible: this is because existing loans are only very seldom accelerated. Instead, new loans (if any) are made at lower LTVs while old loans keep existing, and so the delevering of the entire market happens more gradually. However, the data does show that, as predicted by the Bernanke-Gertler model, a significant delevering takes place.

We next turn to the impulse responses to shocks to LTV. In the context of the Bernanke-Gertler model, a positive shock to LTV happens endogenously, at the beginning of the cycle when asset values experience a shock (i.e. yields increase). Figure 6 shows the response of yield to such a shock. The marginal response of yield begins at zero, but becomes positive by the second quarter with a peak at that time, followed by a slow reversion towards zero. The confidence bands indicate that this shock is significant. This illustrates the feedback of the Bernanke-Gertler debt cycle. The shock to asset values causes a rise in LTVs, which causes a debt scarcity. The scarcity further depresses asset prices, by lowering the feasibility of investments. This manifests as a rise in yield.

The Bernanke-Gertler model also predicts that debt scarcity leads to a lack of liquidity in asset markets. We therefore next consider the impact on volume of the initial LTV shock. This impulse response is shown in Figure 7. The left panel shows the marginal effect of the shock to LTV, which immediately is negative, and then reverts to a zero- and slightly positive effect. Due to the short duration of the significantly negative effect and the uncertain nature of the marginal effects at longer horizons we also consider the cumulative response function for this relationship. This is shown in the right panel. This shows that trading volume is significantly decreased for at least eight quarters, and then reverts back to its original level. These results are consistent with the predictions of the Bernanke-Gertler model: the onset of the debt cycle causes a loss of liquidity in asset markets. Liquidity eventually recovers as the cycle tends toward its bottom, in that buyers begin to purchase distressed assets at low prices. This happens when prices have either fallen enough that all-equity deals become attractive, or new lenders have entered the market.

The uncertain nature of the marginal effects for volume, in conjunction with significant cumulative effects that support the debt cycle suggests a certain stickiness in volume, which takes some time to adjust. This is plausible due to the long transaction time involved in commercial property; recall that two to three quarters is typical here. As the debt cycle is set in motion, initially only new transactions will be affected, and so it will take some time before the effect is actually visible in market-wide volume.

Figure 8 shows the impact of a shock to yield on volume. This impulse-response function has a similar shape to the one for LTV on volume (Figure 7), with an initial negative effect, and then a reversion to positive territory. This is again in line with the Bernanke-Gertler model. As shown, the LTV shock affects yield and so these will happen nearly simultaneously. In fact, while debt scarcity will lead to a loss of liquidity in the Bernanke-Gertler world, simply declining asset prices will lead to the same outcome. As with the variance decomposition for volume, this result in isolation could be due to a variety of factors that cause yield expansions. However, in conjunction with the impulse-response of LTV on volume presents strong evidence for this portion of the Bernanke-Gertler effects.

Figure 9 shows the impact on LTV of a shock to volume. By default, the function shows a positive shock, which leads to a short-term decrease in LTV (which, however, for us is not significant) and a later significant increase. In the onset of the debt cycle, the shock to volume is negative, and so the impulse response would show an initial increase in LTV (the mechanical increase discussed earlier) followed by a subsequent decrease as lending standards are tightened. Given that the economic relationship between liquidity and LTV is predicated on the idea that liquidity affects yields, and yields in turn affect volume, it is plausible that this direct relationship looks weak, as it does in this case.

Lastly, Figure 10 shows the effect of a shock in the risk-free rate on LTV. The effect here is not statistically significant so we do not emphasize this result. However, a positive shock to the risk-free rate yields consistently negative point estimates for marginal effects in LTV, which is plausible with intuition: all else equal, a higher risk-free rate should lead to less borrowing in the market. However, leverage is affected by a variety of other factors, and so this relationship is noisy.

4.3 Flight to Quality

Another feature of the Bernanke-Gertler model we can test here is *flight to quality.* This phenomenon happens in the downward debt cycle, in that, as debt becomes more scarce, only entrepreneurs that engage in less risky projects can secure loans. Thus debt capital is deployed to less productive projects. We can test this feature in our natural laboratory: empirically, this would manifest in such a way that in a delevering, riskier portions of the market should delever first, and less risky markets later.

To model this, we divide risk by types of geographic markets into *Core* and *Non-Core*.[32] Empirically, we define as *Core* markets the ten largest Core-Based Statistical Areas (CBSAs) as measured by average NCREIF portfolio value. To set up a wide-enough split along the lines of investment quality, we define as our comparative sample of *Non-Core* markets the ten largest CBSAs outside the top-fifty. Table 1, Panels B and C define these two sets of CBSAs. We then calculate average LTV ratios for properties located in each respective set of CBSAs and regress quarterly changes in LTV in *Core* MSAs at time t ($\Delta Core.LTV_t$) on an intercept and quarterly changes in LTV in *Non-Core* MSAs the previous quarter ($\Delta Non.Core.LTV_{t-1}$). To only consider periods of delevering, we only use observations for which the two-quarter moving average in $\Delta Non.Core.LTV$ is negative. We use the moving average in order to filter out noise observations in which there is a short-lived idiosyncratic decrease in leverage, and instead focus on more meaningful delevering events. Under *flight to quality* we should see delevering in our *Non-Core* set of markets lead delevering in our *Core* set of markets; in other words, we should see a positive coefficient in the time-displaced regression.

Since *flight to quality* is likely a non-linear effect that becomes especially pronounced in strong delevering events, we also run an augmented version of the previous model, where we add a dummy variable $Quint1$ equal to 1 if the value of $\Delta Non.Core.LTV$ is in the bottom quintile of its distribution, and 0 otherwise. We include this dummy by itself, as well as interacted with $\Delta Non.Core.LTV$. This approach is essentially a threshold regression.

Table 3 shows the results from this regression. In Model 1, we find a positive coefficient for $\Delta Non.Core.LTV$, which, however, is not quite significant at the 5% level (t-statistic of 1.93 which corresponds to a p value of .058). In Model 2, on the other hand, we find a positive and strongly significant coefficient (t statistic of 2.85) on the interacted variable $\Delta Non.Core.LTV_{t-1} \times Quint1$. The $\overline{R^2}$ for Model 2 is .20, compared to .04 for Model 1, indicating that with this non-linearity we are able to explain a substantial fraction of this relationship. This presents strong evidence for flight to quality, since it indicates that especially in an event of pronounced deleveraging, debt capital flees first from riskier markets, and only later from less risky ones.[33]

4.4 Low-Leverage Entrepreneurs (ODCE Funds)

The Bernanke-Gertler model predicts that the downward debt cycle eventually also affects low-leverage entrepreneurs, since knock-on effects in capital markets eventually affect all assets. The competing hypothesis would be that well-capitalized low-leverage investors can actually profit in downturns, acting as buyers of last resort, and profiting from the purchase of assets at fire-sale prices. To disentangle these hypotheses we now investigate the debt cycle for Core Open-Ended (ODCE) funds. Recall that this group of funds pursues conservative ("Core") strategies and commits to keeping low leverage.

[32]The economics of this distinction are discussed in Section 2.1.

[33]With a dummy that indicates the 30th rather than the 20th percentile, the results are largely maintained, although more noisy, with a p value of .06. These results are not tabulated but available upon request.

To investigate these low-leverage entrepreneurs, we re-estimate our basic VAR for the sample of properties owned by ODCE funds. Specifically, we recompute the state variables *log.yield*, *ld.noi*, and *log.vol* using only properties held by ODCE funds. As mentioned above, in order to compute yields for this group of funds, we are forced to use appraisals, where transaction prices are not available. The implications of this are discussed in Section 3.2.

For *log.ltv* we keep the previous specification, using industry-wide loan-to-value ratios. This is warranted in that there is no capital-market segmentation between the properties held by ODCE funds and those held by other funds. The LTV variable is designed to capture the overall scarcity of debt in the capital market, which should drive the effects of the debt cycle. Keeping the same definition of this variable when investigating low-leverage players then exactly allows us to determine to what extent these entrepreneurs are affected by the knock-on effects from the overall capital market in which they operate, just like the low-leverage entrepreneurs in the Bernanke-Gertler model. The risk-free rate remains the same.

As before, we begin with the forecast-error variance decomposition results, and then look at the impulse response functions from this VAR. Figure 11 and Table 4, Panel A, show the variance decomposition for yield. As before, this variable is very persistent. As before, however, the next largest driver of yield over most of the prediction horizon becomes LTV. Thus, as before, LTV is the single biggest driver of innovations in yields. To begin with, this rejects a possible null hypothesis that low-leverage investors are unaffected by the debt cycle. For ODCE funds, this is the case from four quarters forward, while for the full sample this was already the case from three quarters forward. This is plausible from economic intuition, as properties held by low-leverage funds are not immediately affected by a debt scarcity, but only once the debt cycle deepens. The maximum proportion of variance explained by LTV for ODCE funds is actually about ten percentage points higher than for the whole sample (above 27% versus around 17%), while the persistence (i.e. the variance of yield explained by itself) is approximately ten percentage points lower. However, as the impulse responses will show, the overall variation for these funds is lower. In addition, *ld.noi*, the cash-flow growth variable, is more important for these funds. This, too, is plausible, as ODCE funds tend to purchase properties which allow for more passive and income-driven strategies and the properties they hold tend to be priced accordingly. The strong effect of LTV on yield looks consistent with a hypothesis of knock-on effects for these funds. However, the impulse-response functions will paint a clearer picture.

We next examine the forecast-error variance decomposition for volume.[34] This is shown in Figure 12 and Table 4, Panel B. We note here too that LTV is an important driver of variations in volume for these funds, accounting for around 12% of variation. This is about 5 percentage points more than for the whole sample. Once again, however, we note that the overall variation for

[34]We do not report an FEVD for LTV in this case. This is because, as stated, LTV is industry-wide (to measure debt scarcity) while all other variables of interest are computed within the set of ODCE funds. It would be difficult to argue that effects within a low-leverage market segment drive industry-wide debt scarcity.

these funds is smaller, and so the effect should be about comparable. Once again, a possible null that these low-leverage entrepreneurs are unaffected by the debt cycle can be rejected. Further, for ODCE funds, volume shows more persistence and a lower dependence on yield than for the full sample.

The first impulse-response function we examine is that of LTV on yield.[35] This is shown in Figure 13. The impulse response here is persistently positive over the entire horizon, with significant effects between about three and eight quarters, as well as briefly around 15 quarters. Comparing this figure with the same impulse response for the entire sample (Figure 6) we find some important differences. For the full sample, the initial effect is more immediate, and much larger, reaching a maximum of more than six basis points after only two quarters, compared to an initial maximum of under two basis points after four quarters, for ODCE funds. The response for the whole sample then reverts to around two basis points by around ten quarters, while that for ODCE funds remains in that range throughout. This contrast is very much consistent with economic intuition: properties with higher leverage should react strongly and immediately to the rise in LTV; the higher-leverage segment of the market is the one that is directly affected by the scarcity of debt. It is in this segment where investments immediately become infeasible, and where we would see loan accelerations by banks (if any) leading to fire sales. In contrast, the low-leverage investors in the market initially have little direct effect. The effect on the low-leverage investors comes only from the overall market downturn, which takes longer to set in. Once this downturn has deepened enough, the entire market is equally affected.

This shows that the positive LTV shock at the outset of the debt cycle also negatively affects asset values in this low-leverage segment of the market, exactly in the way predicted by the Bernanke-Gertler model. However, whether ODCE funds now purchase distressed assets as buyers of last resort, or rather take a similar loss to their own assets as more levered funds do may yet remain unclear.[36]

The first way to disentangle these two hypotheses is through economic reasoning. In order for ODCE funds to act as buyers of last resort and profit from fire sales, these funds would need to be able to raise new money in a deepening downturn, at a time when neither non-ODCE funds (nor banks, for that matter) are able to do so. It is difficult to argue why they might be able to do this. On the contrary, ODCE funds' open-ended structures are likely to cause a capital constraint for these funds as well, in that investors will likely request redemptions in a downturn, in an effort to pull their money out of CRE. As discussed in Section 2.1, at this time these funds would thus face *redemption queues* which would make them unable to buy new assets. Even if they received contributions at this time, these would need to be used primarily to honor redemptions.

We also attempt to disentangle these two hypotheses empirically. To do so, we run a regression

[35] As with the FEVD, we do not consider any responses on LTV for this part.

[36] Although in the latter case one might be more likely to see yields revert sooner than they do.

of changes in ODCE funds' real estate assets on the left-hand side,[37] on changes in our LTV variable (including up to four lags). We find a negative coefficient for LTV, significant at the .1% level, and a negative coefficient for LTV lagged by one quarter, significant at the 1% level.[38] If ODCE funds acted as buyers in high-LTV situations, we would find positive coefficients here. Thus, these results strongly support the hypothesis that low-leverage investors suffer knock-on effects from the debt cycle in this market.

The final impulse-response we consider here is the response of volume to a shock in LTV. These are shown in Figure 14. The responses (both marginal and cumulative) are qualitatively extremely similar to those for the entire sample (Figure 7). This indicates that liquidity in the market segment of properties held by low-leverage investors is similarly affected by the leverage cycle, as it is for the entire industry.

The results shown here thus present strong evidence that, as in the Bernanke-Gertler model, low-leverage investors, through knock-on effects in the capital market, are also affected by the debt cycle.

We now further explore the mechanism of redemption queues in preventing ODCE funds from acting as buyers of last resort in a downward debt cycle and thus from profiting from fire sales. Regrettably, our data does not allow us to observe redemption requests or size of redemption queues. While the data does show realized redemptions, this quantity is not informative in this respect: the limiting mechanism for ODCE funds is not the redemptions they have already made, but the pent-up demand for redemptions, which they cannot honor at a specific point in a downturn. However, it is known that as a buffer to honor some amounts of redemption, ODCE funds hold cash reserves. These reserves are observable to us. We can therefore track the evolution of cash reserves as the debt cycle sets in, in order to produce some evidence for the redemption-queue mechanism.

To explore this, we augment the previous VAR by an additional state variable, namely cash reserves. NCREIF provides this data, defined as "the fraction of a fund's assets that consists of cash." As with the other state variables, we use the natural logarithm of this series in the VAR. This data is only populated starting from the beginning of 2000. We therefore estimate this augmented VAR over this shortened time period. Due to the shortened time horizon, we do not have enough power for a VAR with eight lags, and therefore resort to a four-lag VAR for this investigation.

Figure 15 and Panel C of Table 4 provides the variance decomposition for the log of cash for the core open-end funds. As with other state variables, cash holdings are highly persistent, at least at short forecast horizons (below 9 quarters). At longer horizons, the yield is actually the primary driver of cash holdings, even exceeding own-variable persistence, and explaining up to 33 percent of variation. This result is consistent with the hypothesis of ODCE funds' managing cash

[37] To account for the changing number of funds that NCREIF tracks, we also specify this variable as changes in real estate assets divided by the number of funds. Further, we specify real estate assets as either gross (i.e. including any debt) or net (i.e. not including debt). Our results are qualitatively maintained for all specifications.

[38] For brevity these results are not tabulated, but are available from the authors.

holdings in order to be able to honor redemptions, according to market conditions. The way we would expect LTV (i.e. the measure of debt scarcity in the overall market) to be related here is primarily through its effect on yield, since these funds take no- or very little debt themselves: in any market downturn (whether caused by a scarcity of debt or by another factor), we would expect ODCE funds to adjust their level of cash to manage eventual redemption requests. An onset of the downward debt cycle simply constitutes one possible reason for a market downturn. Thus, the result that LTV explains about 15-20 percent of variation is in line with this, as other things may also drive downturns. Conversely, however, the fact that a significant fraction of cash holdings of ODCE funds is still explained by industry-wide LTV lends strong support to the hypothesis that ODCE funds are affected by the knock-ons of debt cycles, and some support to the hypothesis that redemptions act as an important mechanism in driving this.

Figure 16 shows the impulse response of cash reserves to a positive shock in yield. This response is significantly positive, reaching a peak around eight to ten quarters, and then reverts back towards zero. This response is consistent with a hypothesis that, at the onset of a market downturn ODCE funds begin to hoard cash, in order to be able to honor redemptions deeper in the cycle, at which point these redemptions slowly exhaust their cash reserves.

Once again, this is a general shock to yield and therefore only shows how these funds generally behave in downturns. However, this should be sufficient to support to the importance of the redemptions mechanism in driving behavior of ODCE funds: ultimately a debt-induced downturn is nothing but a downturn. On the other hand, to illustrate that debt-induced downturns are no different, we also show the impulse response to cash of a shock in LTV (Figure 17). This impulse response is qualitatively very similar to that from yield, but more noisy. This is consistent with economic intuition, in that, once again, the effect of LTV on ODCE funds is always a function of the effect of LTV on the yield of their properties.

Thus, we show here that early in a downturn, ODCE funds hoard cash, which is then depleted. Earlier evidence suggests that ODCE funds are not using cash to buy (now) lower-priced assets and profit from fire sales. Instead, cash seems to be used to cover redemptions, or possibly recapitalize properties.

In this subsection we have thus presented strong evidence that, as in the Bernanke-Gertler world, low-leverage entrepreneurs are also affected by a downward debt cycle, once the cycle deepens to enough of an extent. The value of the assets of low-leverage investors also declines; the argument with regards to redemption queues and the evidence on cash reserves shows the mechanism by which these entrepreneurs also lose external funding at this point and are therefore also unable to invest. This is an important prediction of the Bernanke-Gertler model and we are able to empirically document this here.

5 Conclusion

The Bernanke-Gertler debt cycle constitutes an important economic mechanism and an extremely appealing theory. Yet it has so far been difficult to test this mechanism empirically and quantify its effect on asset markets. Our study contributes to the literature by setting up a natural laboratory in a large and mature asset class that is ideally suited to testing this paradigm. To do this, we model Commercial-Real-Estate yields, as conditioned by industry-wide loan-to-value (LTV).

We use a VAR as our empirical tool and consider forecast-error variance decompositions as well as impulse-responses from this estimation. We find that LTV constitutes the primary driver of innovations in yields, and vice versa, thus showing the importance of this feedback cycle to the asset market. Impulse-responses are as predicted by the model. We further find evidence for *flight to quality*, as well as knock-on effects in asset markets which negatively affect the asset values of low-leverage entrepreneurs, as predicted in the Bernanke-Gertler paradigm.

Our study thus underlines the crucial importance of a well-functioning debt market to a capital market, as well as the debt market's role in accelerating capital-market cyclicality. A link between capital markets and output is already well established in the literature. Therefore our study implicitly also highlights the crucial importance of a well-functioning debt market to overall economic output.

A Appendix: Computation of Yields from NCREIF TBI Index Returns

This section illustrates the method we use to compute the weighted-average cash-flow yield series for the NCREIF portfolio, using the Transactions-Based Index (TBI). NCREIF offers two return figures: *tot.ret* and *app.ret*. *tot.ret* is total return which includes income- and price-appreciation returns, and *app.ret* is holding period return excluding income. Conceptually, we have:

$$tot.ret_t = \frac{P_t + C_t}{P_{t-1}} - 1 \tag{5}$$

$$app.ret_t = \frac{P_t}{P_{t-1}} - 1 \tag{6}$$

Here, P_τ is asset price at the end of period τ and C_τ is cash flow paid out over period τ. Thus, the cash-flow yield $y_t = C_t/P_t$ for our weighted portfolio is constructed as

$$y_t = (tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} \tag{7}$$

This is because

$$\begin{aligned}(tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} &= \left[\frac{P_t + C_t}{P_{t-1}} - 1 - \frac{P_t}{P_{t-1}} + 1\right] \times \frac{P_{t-1}}{P_t} \\ &= \frac{C_t}{P_{t-1}} \times \frac{P_{t-1}}{P_t} \\ &= C_t/P_t\end{aligned} \tag{8}$$

Here $tot.ret_t$ and $app.ret_t$ are the total returns and price returns respectively, to NCREIF TBI over quarter t. P_t is the index level (i.e. pseudo-price) at the end of quarter t, and C_t the total cash flow paid out over quarter t, to someone holding one share of the index.

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Table 1: Summary Statistics for NCREIF Data

This table presents summary statistics for the NCREIF dataset. Panel A shows statistics on the total size of the portfolio tracked by NCREIF, followed by value-weighted Loan-to-Value ratios (LTV) across the total portfolio, the subset of properties that use any debt, and the subset of properties owned by Core Open-Ended Funds. Panels B and C present the names and average portfolio values of the ten largest Core-Based Statistical Areas (CBSAs) and the ten largest CBSAs outside the set of top-50 CBSAs. All rankings are done by total NCREIF portfolio value in a given market and quarter, averaged across time.

Panel A: Portfolio Values and LTVs.

	Mean	**Stdev**	**1st Quartile**	**Median**	**3rd Quartile**
Total Portfolio Value (Million $)	143,893	158,462	23,794	66,217	247,070
Total LTV	0.1906	0.1057	0.1315	0.1884	0.2795
LTV Conditional on Using Debt	0.4336	0.07882	0.3736	0.4625	0.4785
LTV of Core Open-Ended (ODCE) Funds	0.1205	0.09106	0.03788	0.09496	0.2089

Panel B: Top-Ten CBSAs.

CBSA Name	**Average Portfolio Value (Million $)**
NY-NJ- New York-Jersey City-White Plains	14,066
DC-VA-MD-WV-Washington-Arlington-Alexandria	11,562
CA-Los Angeles-Long Beach-Glendale	10,690
IL-Chicago-Naperville-Arlington Heights	8,368
CA-San Francisco-Redwood City-South San Francisco	5,372
TX-Dallas-Plano-Irving	5,170
TX-Houston-The Woodlands-SugarLand	4,999
WA-Seattle-Bellevue-Everett	4,643
GA-Atlanta-Sandy Springs-Roswell	4,544
MA-Boston	4,016

Panel C: Ten Largest Non-Top-50 CBSAs.

CBSA Name	**Average Portfolio Value (Million $)**
NH-Rockingham County-Strafford County	427
FL-Jacksonville	414
NJ-Camden	381
UT-Salt Lake City	375
NV-Reno	355
RI-MA-Providence-Warwick	327
HI-Urban Honolulu	323
PA-Pittsburgh	316
MI-Warren-Troy-Farmington Hills	305
TN-Knoxville	292

Table 2: Forecast-Error Variance Decompositions for Full-Sample VAR

This table shows the forecast-error variance decomposition for *log.yield* (Panel A), *log.ltv* (Panel B), and *log.vol* (Panel C) from the VAR estimated over state variables aggregated over all properties in the sample. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

	Panel A: *log.yield*					**Panel B:** *log.ltv*				
Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.vol*	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.vol*
1	1	0	0	0	0	0.072888	0.00898	0.00366	0.914473	0
2	0.959735	0.035409	$9.6e-05$	$4e-06$	0.004755	0.058191	0.016843	0.003447	0.919045	0.002474
3	0.842575	0.04366	0.009705	0.096011	0.008049	0.055332	0.02425	0.005927	0.91291	0.001581
4	0.829561	0.043247	0.015161	0.102077	0.009954	0.067913	0.035021	0.006757	0.887332	0.002978
5	0.799988	0.035804	0.016127	0.133621	0.01446	0.057484	0.037498	0.007843	0.883	0.014174
6	0.778087	0.044741	0.014664	0.148726	0.013782	0.049017	0.052748	0.008287	0.869585	0.020362
7	0.74444	0.0446	0.033675	0.157749	0.019536	0.041476	0.06055	0.012899	0.862749	0.022326
8	0.722071	0.05199	0.039412	0.167888	0.018639	0.036075	0.070527	0.016061	0.855897	0.02144
9	0.720449	0.059594	0.038225	0.162663	0.019069	0.035838	0.07638	0.017774	0.847544	0.022464
10	0.717284	0.062445	0.038193	0.162147	0.019932	0.042685	0.080747	0.019196	0.835779	0.021593
11	0.700655	0.073973	0.043098	0.162798	0.019475	0.054483	0.08075	0.020307	0.82412	0.020339
12	0.679864	0.089712	0.04346	0.162313	0.02465	0.070342	0.078157	0.020204	0.811978	0.019319
13	0.678374	0.093653	0.042847	0.160657	0.024469	0.087397	0.075477	0.020785	0.797043	0.019298
14	0.660439	0.106285	0.041778	0.165253	0.026244	0.101906	0.072687	0.021835	0.781902	0.021669
15	0.643577	0.114737	0.048299	0.164563	0.028825	0.114388	0.070052	0.022816	0.766296	0.026448
16	0.629627	0.1233	0.047862	0.167649	0.031562	0.123052	0.067315	0.023355	0.753018	0.033261
17	0.623862	0.126993	0.047161	0.168691	0.033293	0.128074	0.065337	0.024497	0.740794	0.041298
18	0.612977	0.131158	0.048112	0.169284	0.038469	0.132022	0.063532	0.025396	0.730326	0.048725
19	0.603408	0.132983	0.052984	0.169342	0.041283	0.134957	0.062197	0.026247	0.720831	0.055768
20	0.593392	0.139462	0.052313	0.170119	0.044713	0.137121	0.061229	0.026988	0.712388	0.062273
21	0.589764	0.141039	0.052188	0.169276	0.047733	0.138745	0.060611	0.027915	0.70419	0.06854
22	0.58417	0.143879	0.052596	0.168721	0.050635	0.140662	0.059844	0.028738	0.69586	0.074896
23	0.57652	0.147503	0.055156	0.166888	0.053934	0.142226	0.059141	0.029589	0.68778	0.081264
24	0.569808	0.151704	0.054503	0.165026	0.058959	0.143611	0.058313	0.030041	0.680295	0.08774

Panel C: *log.vol*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.vol*
1	0.044778	0.01033	0.00991	0.026141	0.908841
2	0.063527	0.049605	0.016433	0.053177	0.817258
3	0.060908	0.054806	0.026349	0.075627	0.782311
4	0.059136	0.052702	0.025572	0.082427	0.780163
5	0.050344	0.071424	0.023598	0.073451	0.781182
6	0.05126	0.086155	0.023832	0.079371	0.759383
7	0.136157	0.080993	0.023248	0.069189	0.690413
8	0.157528	0.080716	0.027702	0.066045	0.668009
9	0.165527	0.085147	0.027468	0.067893	0.653965
10	0.190441	0.091641	0.027854	0.065537	0.624527
11	0.23834	0.08814	0.027056	0.065168	0.581296
12	0.256614	0.086242	0.026852	0.064063	0.566228
13	0.261259	0.093994	0.026509	0.063317	0.55492
14	0.277362	0.095843	0.025744	0.062627	0.538424
15	0.292836	0.100909	0.028297	0.061885	0.516072
16	0.301268	0.106609	0.028286	0.060374	0.503462
17	0.304313	0.11492	0.028008	0.060042	0.492717
18	0.307638	0.124553	0.0281	0.061699	0.478009
19	0.314285	0.132368	0.028424	0.061384	0.463539
20	0.320309	0.136543	0.029025	0.061786	0.452337
21	0.318522	0.145156	0.028572	0.06433	0.44342
22	0.319909	0.152895	0.02782	0.06601	0.433366
23	0.324285	0.155815	0.027258	0.06724	0.425402
24	0.32412	0.160868	0.027575	0.069436	0.418001

Table 3: Regressions for Flight to Quality

Dependent variable: $\Delta Core.LTV_t$. This table presents results of a set of regressions that model Flight to Quality. The dependent variable ($\Delta Core.LTV_t$) is the quarter-to-quarter change in average loan-to-value (LTV) ratio across the portfolio of properties located in *core* markets (defined here as top-10 MSAs in the NCREIF portfolio). The independent variables consist of: $\Delta Non.Core.LTV_{t-1}$ is the quarter-to-quarter change in average LTV across a set of *non-core* markets (the ten largest non-top-50 MSAs), lagged by one quarter; $Quint1$ a dummy equal to 1 if in quarter t the value of $\Delta Non.Core.LTV$ is in the bottom quintile of the distribution of values for this variable. For this regression, we use only time periods of delevering in non-core MSAs, defined as quarters in which the two-quarter moving average $\Delta Non.Core.LTV$ is negative.

	Model 1	**Model 2**
(Intercept)	$4e-04$	0.0031
	(0.08)	(0.42)
$\Delta Non.Core.LTV_{t-1}$	0.2676	0.0289
	$(1.93)^{\circ}$	(0.17)
$Quint1$		-0.013
		(-1.24)
$\Delta Non.Core.LTV_{t-1} \times Quint1$		0.7464
		$(2.85)^{**}$
	N: 72	N: 72
	$\overline{R^2}$: 0.0369	$\overline{R^2}$: 0.202
	F: 3.72	F: 6.99

$^{\circ}$: significance level < 10%. *: significance level < 5%. **: significance level < 1%. *** : significance level < 0.1%.

Table 4: Forecast-Error Variance Decompositions for VAR of Core Open-Ended Funds

This table shows the forecast-error variance decomposition for *log.yield* (Panel A), *log.ltv* (Panel B), and *log.cash* (Panel C) from the VAR estimated over state variables aggregated over properties owned by ODCE funds. The state variables for the VAR system in Panels A and B are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). This VAR system uses 8 lags. The VAR system for Panel C adds *log.cash* to the state variables above. Due to the shorter time series availability, the VAR system for Panel C uses 4 lags. All variables are constructed as either natural logarithms or differences of logarithms.

	Panel A: *log.yield*					**Panel B:** *log.volume*				
Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.volume*	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.volume*
1	1	0	0	0	0	0.002029	0.000714	0.007795	0.045835	0.943628
2	0.929943	0.004655	0.041194	0.007834	0.016375	0.028476	0.006397	0.019579	0.09351	0.852038
3	0.891661	0.004389	0.050795	0.039156	0.013999	0.025664	0.006212	0.021991	0.128689	0.817445
4	0.794408	0.003072	0.08216	0.092995	0.027365	0.046368	0.01041	0.019905	0.122161	0.801156
5	0.777236	0.004105	0.071647	0.099214	0.047798	0.056028	0.013435	0.024107	0.117641	0.788789
6	0.725758	0.019432	0.082542	0.117392	0.054875	0.064952	0.012484	0.036268	0.132845	0.753451
7	0.702491	0.02396	0.079541	0.139478	0.054531	0.092423	0.013166	0.053046	0.126211	0.715155
8	0.660922	0.029022	0.083518	0.157509	0.069029	0.0953	0.014714	0.050814	0.123409	0.715763
9	0.656716	0.03253	0.078256	0.158127	0.07437	0.103572	0.016766	0.057529	0.12139	0.700743
10	0.624229	0.044144	0.084804	0.16791	0.078914	0.104282	0.018441	0.058716	0.120833	0.697729
11	0.605531	0.051656	0.084159	0.18175	0.076903	0.142562	0.017642	0.056879	0.115553	0.667365
12	0.576811	0.060376	0.090984	0.191958	0.079871	0.143711	0.018301	0.056385	0.118305	0.663297
13	0.56394	0.065103	0.093018	0.198392	0.079547	0.146996	0.018475	0.056253	0.117804	0.660472
14	0.536629	0.072473	0.1033	0.20985	0.077748	0.15308	0.018025	0.054472	0.11809	0.656334
15	0.51813	0.075406	0.105581	0.225941	0.074943	0.16329	0.017761	0.054352	0.116866	0.647731
16	0.497201	0.077902	0.113162	0.237517	0.074218	0.165502	0.018164	0.053732	0.119711	0.642891
17	0.489651	0.078803	0.114367	0.245493	0.071686	0.165704	0.01811	0.053732	0.122345	0.640108
18	0.47322	0.08133	0.121564	0.254501	0.069385	0.172372	0.017942	0.055622	0.122239	0.631826
19	0.464608	0.082303	0.12267	0.263571	0.066848	0.177249	0.01815	0.055386	0.125885	0.623329
20	0.45369	0.084306	0.127285	0.269267	0.065452	0.178006	0.018518	0.059861	0.129223	0.614392
21	0.451084	0.086224	0.127838	0.271541	0.063313	0.177303	0.018687	0.059618	0.137682	0.606709
22	0.442478	0.090189	0.131588	0.274204	0.06154	0.178661	0.019065	0.063083	0.140557	0.598635
23	0.438539	0.093303	0.132017	0.276124	0.060017	0.184711	0.019694	0.064047	0.145245	0.586303
24	0.432768	0.097269	0.134646	0.276577	0.058739	0.182453	0.020629	0.067306	0.152076	0.577535

Panel C: *log.cash*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.volume*	*log.cash*
1	0.008909	0.004021	0.038624	0.056373	0.007579	0.884494
2	0.019703	0.012991	0.030346	0.105674	0.032858	0.798428
3	0.034948	0.025011	0.034985	0.129994	0.025598	0.749464
4	0.065869	0.05893	0.047538	0.151515	0.02109	0.655057
5	0.09885	0.083173	0.052179	0.165237	0.026223	0.574337
6	0.175138	0.08194	0.045077	0.194542	0.035754	0.46755
7	0.224546	0.070308	0.041664	0.214603	0.054719	0.394161
8	0.265079	0.061009	0.054967	0.210491	0.071544	0.33691
9	0.284926	0.062626	0.063168	0.203504	0.089597	0.296179
10	0.300517	0.072665	0.077451	0.190008	0.09655	0.262809
11	0.309457	0.090516	0.081366	0.180129	0.099324	0.239208
12	0.31724	0.109499	0.085678	0.170678	0.096367	0.220539
13	0.322373	0.128165	0.084859	0.165136	0.092323	0.207146
14	0.327437	0.143197	0.083943	0.160909	0.087792	0.196722
15	0.33018	0.155698	0.081582	0.158823	0.084473	0.189243
16	0.332172	0.164717	0.079561	0.157534	0.082582	0.183432
17	0.332454	0.171229	0.077655	0.157256	0.082015	0.17939
18	0.332272	0.175355	0.076167	0.157103	0.082706	0.176396
19	0.331273	0.177884	0.075166	0.157165	0.084007	0.174504
20	0.330258	0.179016	0.074473	0.157087	0.085901	0.173265
21	0.329053	0.179219	0.074232	0.156941	0.087868	0.172687
22	0.328079	0.178818	0.074137	0.156652	0.089871	0.172443
23	0.327188	0.178157	0.074293	0.156313	0.091536	0.172513
24	0.326557	0.177491	0.074428	0.155936	0.092915	0.172674

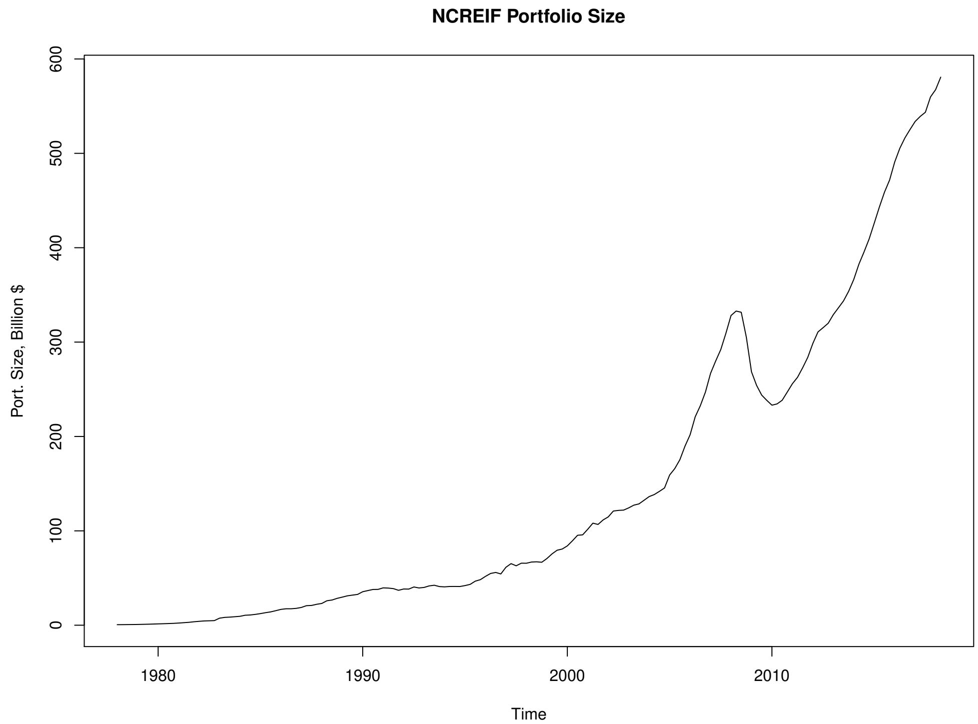

Figure 1: NCREIF Portfolio Size (Billion US $).

This figure shows the historical progression of the size of the NCREIF portfolio, in Billion US Dollars.

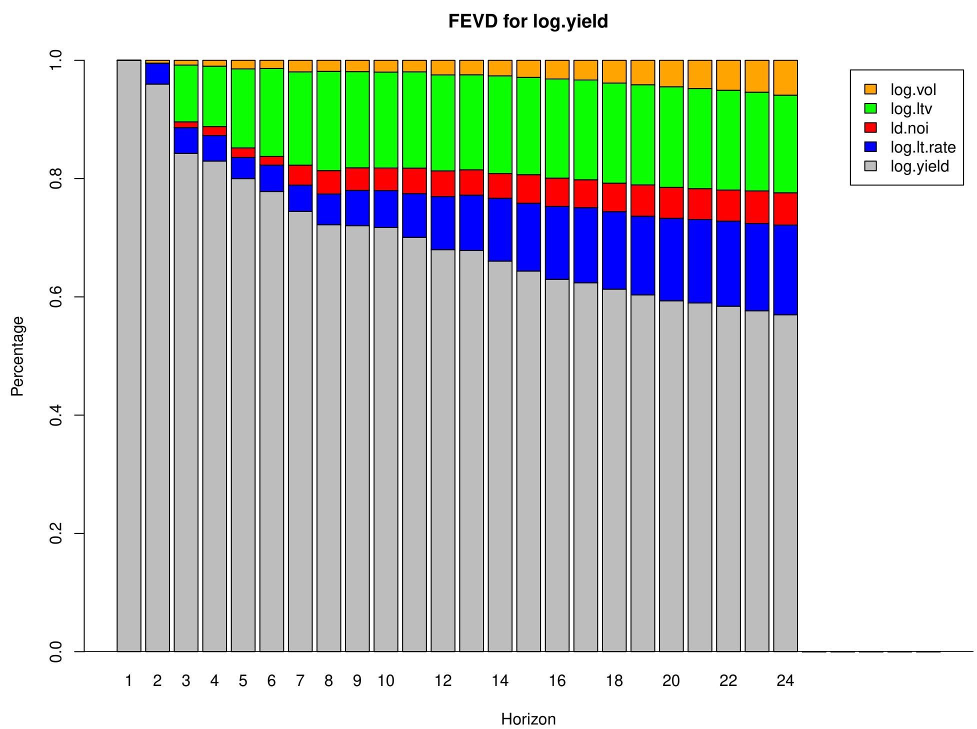

Figure 2: Forecast-Error Variance Decomposition for *log.yield*, full-sample VAR.

This figure shows the forecast-error variance decomposition for *log.yield* from the VAR estimated over state variables aggregated over all properties in the sample. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

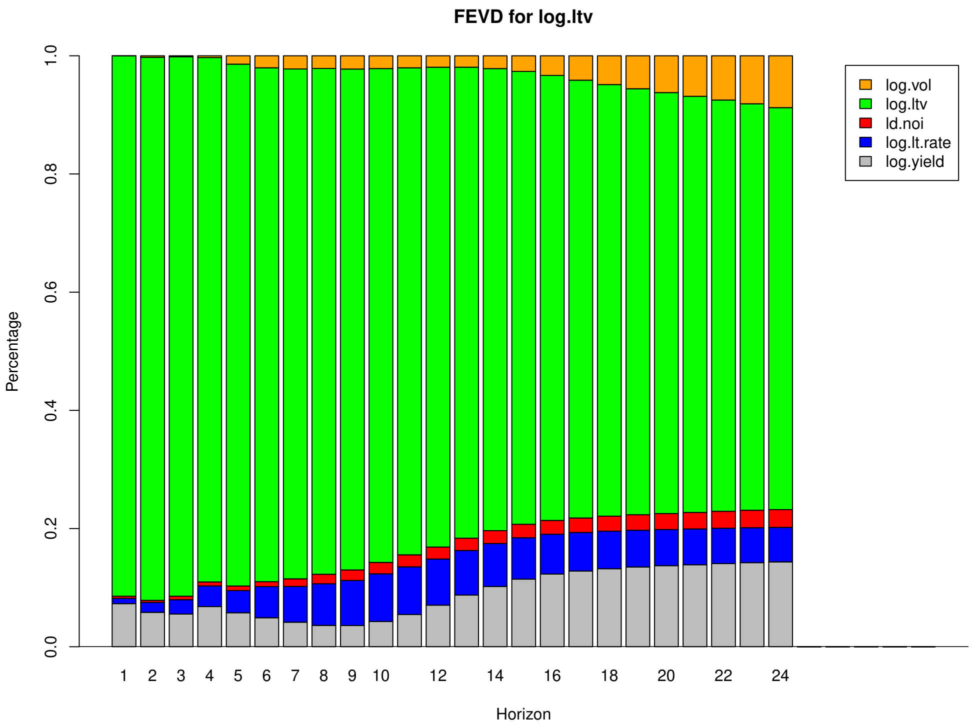

Figure 3: Forecast-Error Variance Decomposition for *log.ltv*, full-sample VAR.

This figure shows the forecast-error variance decomposition for *log.ltv* from the VAR estimated over state variables aggregated over all properties in the sample. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

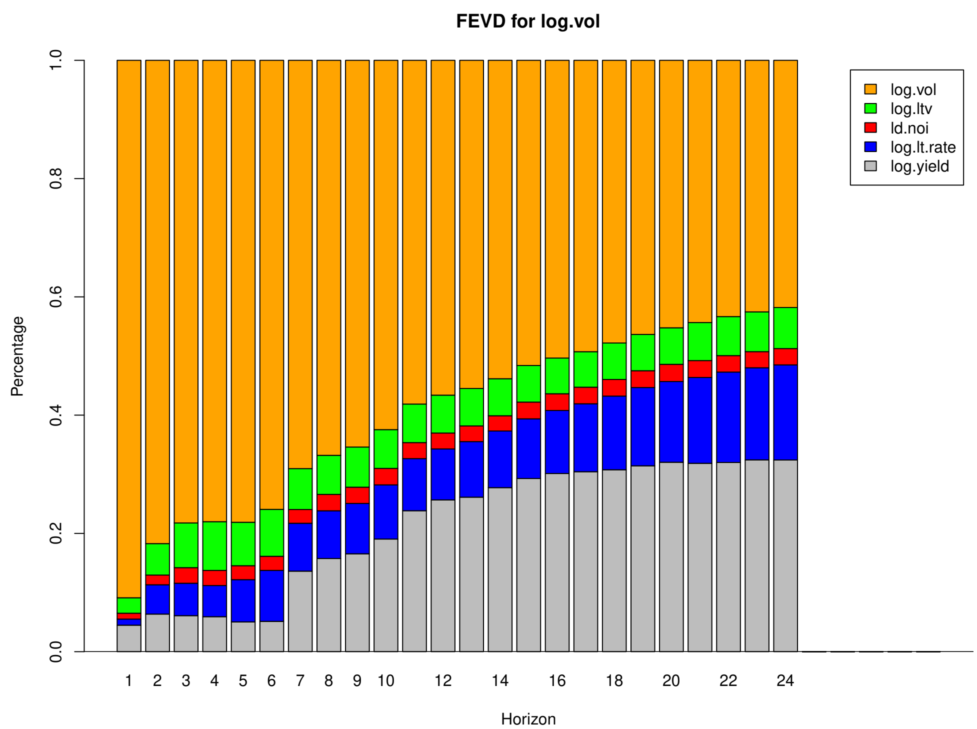

Figure 4: Forecast-Error Variance Decomposition for *log.vol*, full-sample VAR.

This figure shows the forecast-error variance decomposition for *log.vol* from the VAR estimated over state variables aggregated over all properties in the sample. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

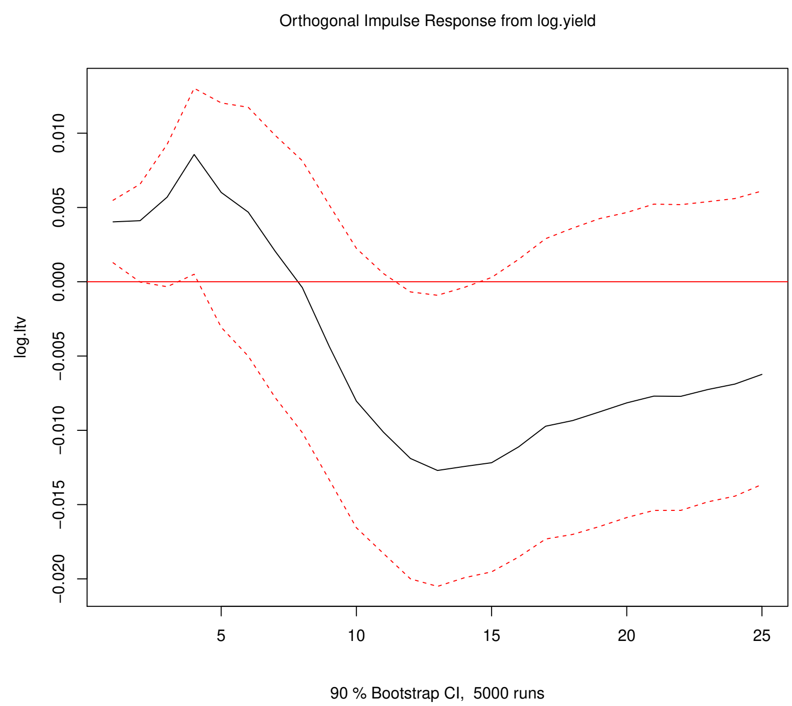

Figure 5: Impulse-Response Function, *log.yield* on *log.ltv*, full-sample VAR.

This figure shows an orthogonal impulse-response function of *log.yield* on *log.ltv*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

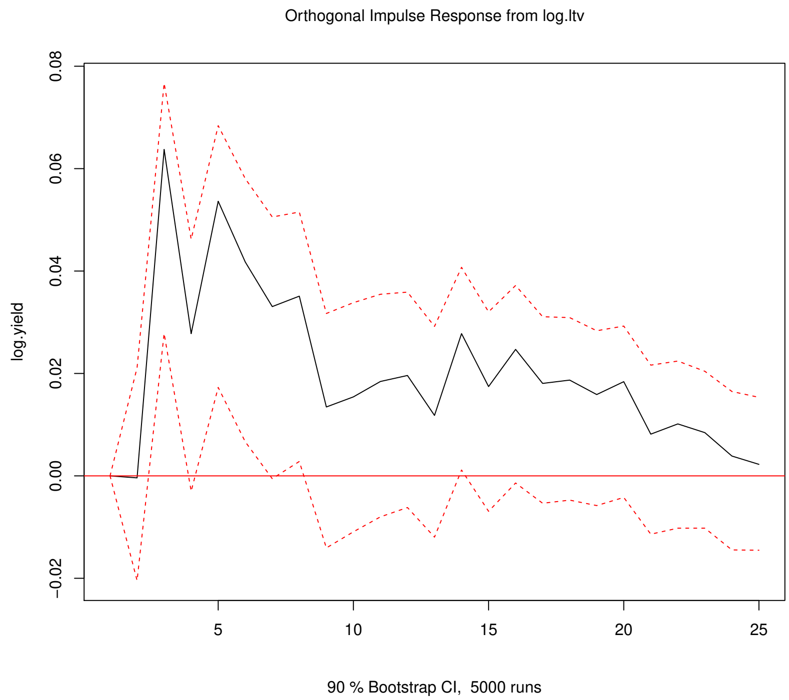

Figure 6: Impulse-Response Function, *log.ltv* on *log.yield*, full-sample VAR.

This figure shows an orthogonal impulse-response function of *log.ltv* on *log.yield*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

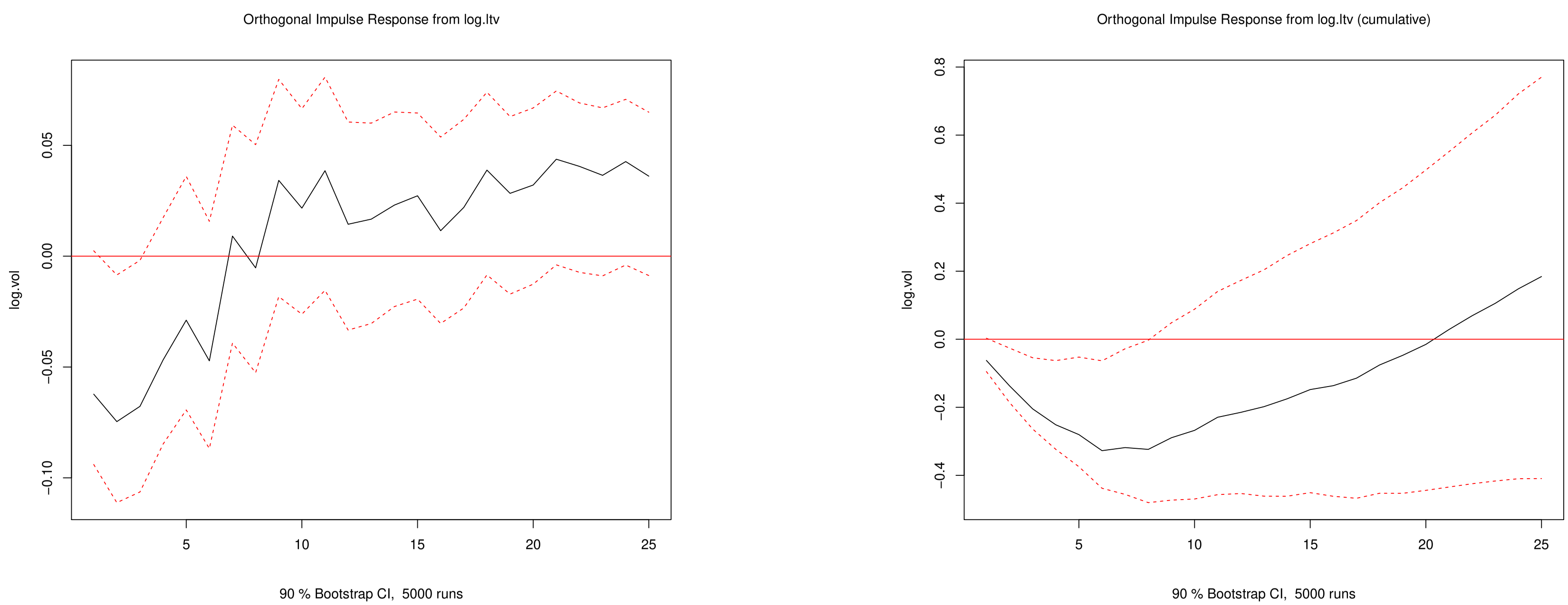

Figure 7: Impulse-Response Function, *log.ltv* on *log.vol*, full-sample VAR.

This figure shows an orthogonal impulse-response function of *log.ltv* on *log.vol*, with the left panel showing the marginal impulse-response function, and the right showing the cumulative. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

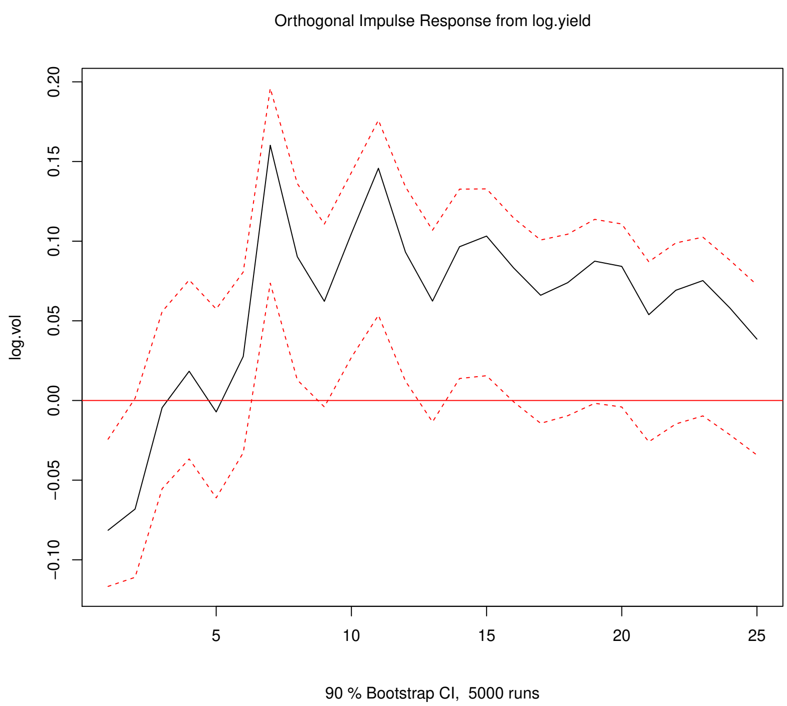

Figure 8: Impulse-Response Function, *log.yield* on *log.vol*, full-sample VAR.

This figure shows an orthogonal impulse-response function of *log.yield* on *log.vol*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

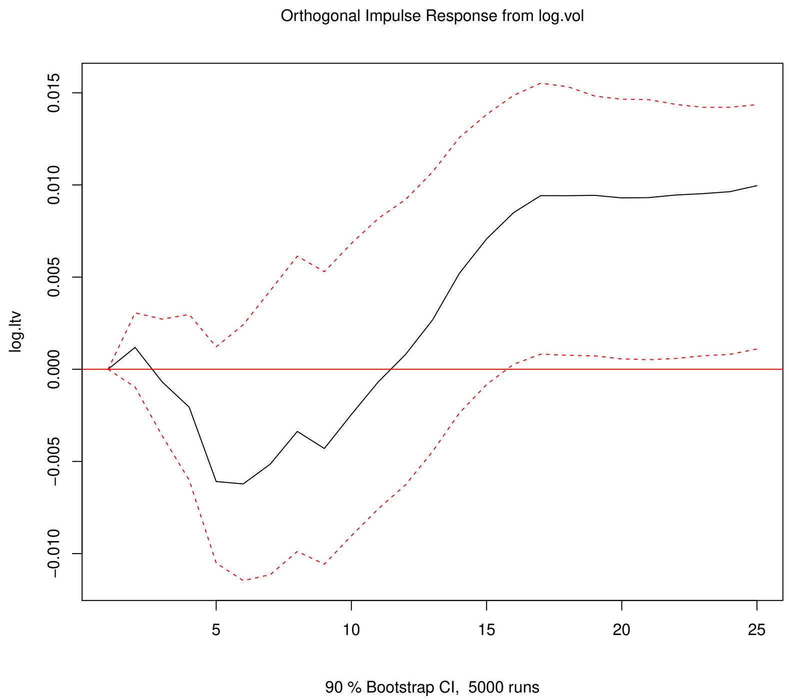

Figure 9: Impulse-Response Function, *log.vol* on *log.ltv*, full-sample VAR.

This figure shows an orthogonal impulse-response function of *log.vol* on *log.ltv*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

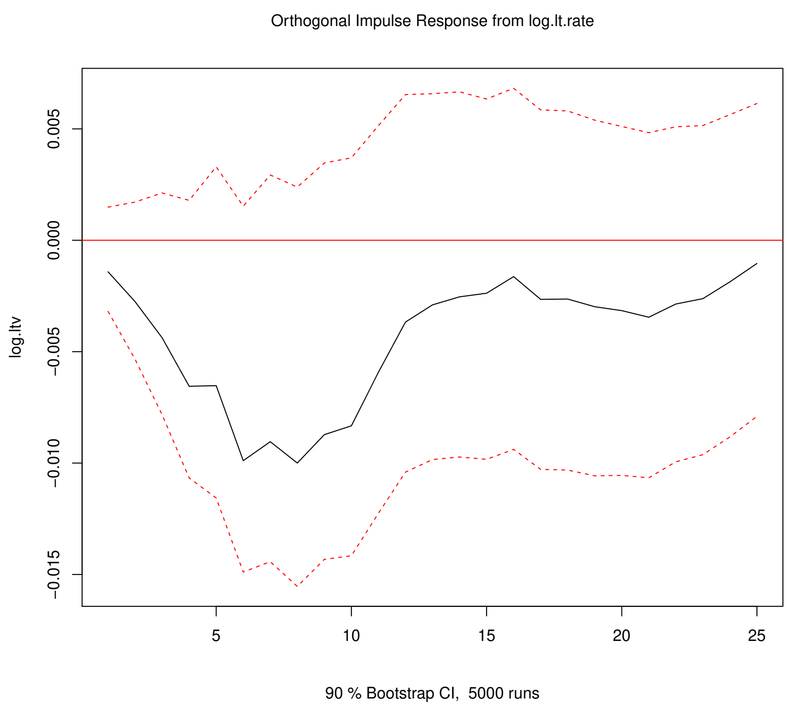

Figure 10: Impulse-Response Function, $log.lt.rate$ on $log.ltv$, full-sample VAR.

This figure shows an orthogonal impulse-response function of $log.lt.rate$ on $log.ltv$. The state variables for the VAR system are $log.yield$ (the cash-flow yield), $log.lt.rate$ (the long-term risk-free rate), $ld.noi$ (the cash-flow growth rate), $log.ltv$ (the loan-to-value ratio of a property), and $log.vol$ (the trading volume). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

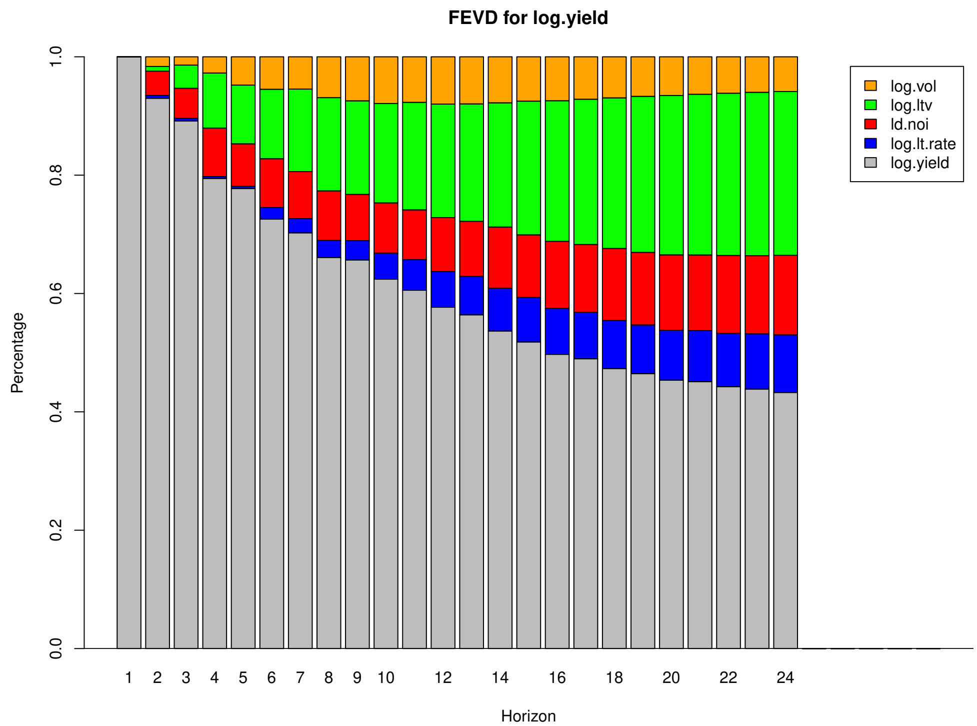

Figure 11: Forecast-Error Variance Decomposition for *log.yield*, Core Open-Ended Funds Only. This figure shows the forecast-error variance decomposition for *log.yield* from the VAR estimated over state variables aggregated over the properties held by Core Open-Ended Funds. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

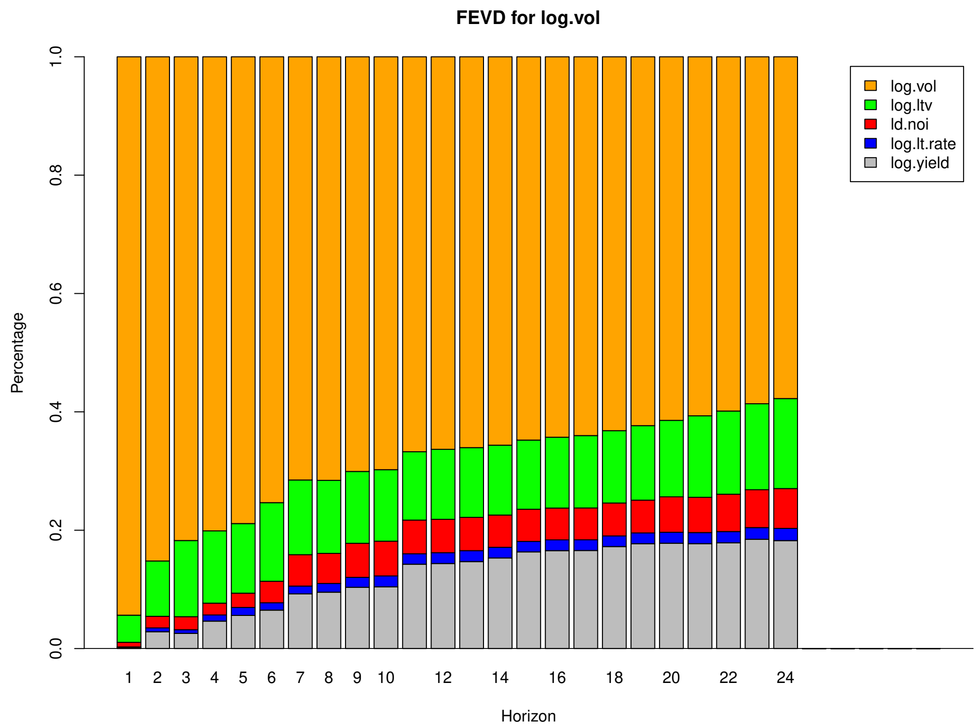

Figure 12: Forecast-Error Variance Decomposition for *log.vol*, Core Open-Ended Funds Only. This figure shows the forecast-error variance decomposition for *log.vol* from the VAR estimated over state variables aggregated over the properties held by Core Open-Ended Funds. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

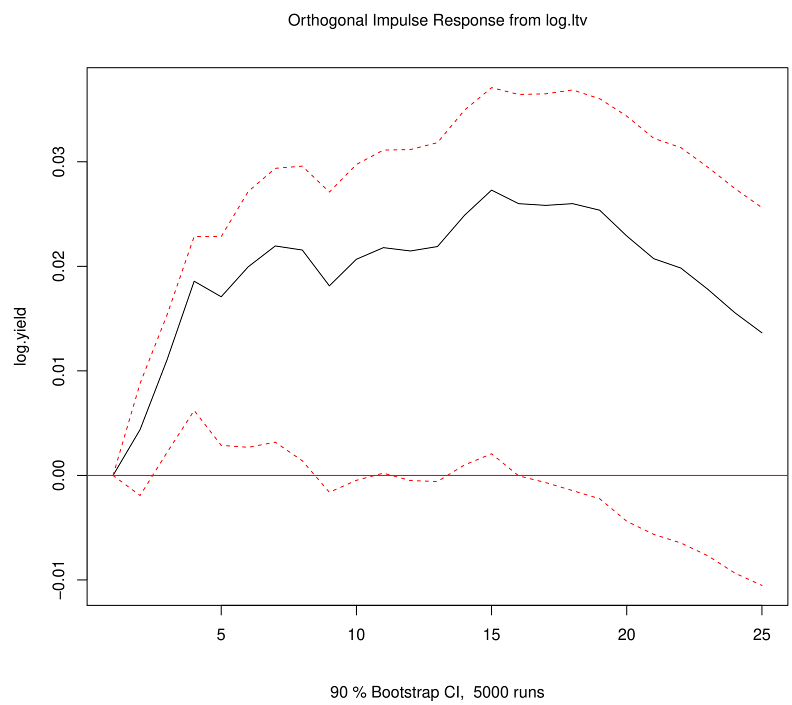

Figure 13: Impulse-Response Function, *log.ltv* on *log.yield*, Core Open-Ended Funds Only.

This figure shows an orthogonal impulse-response function of *log.ltv* on *log.yield*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

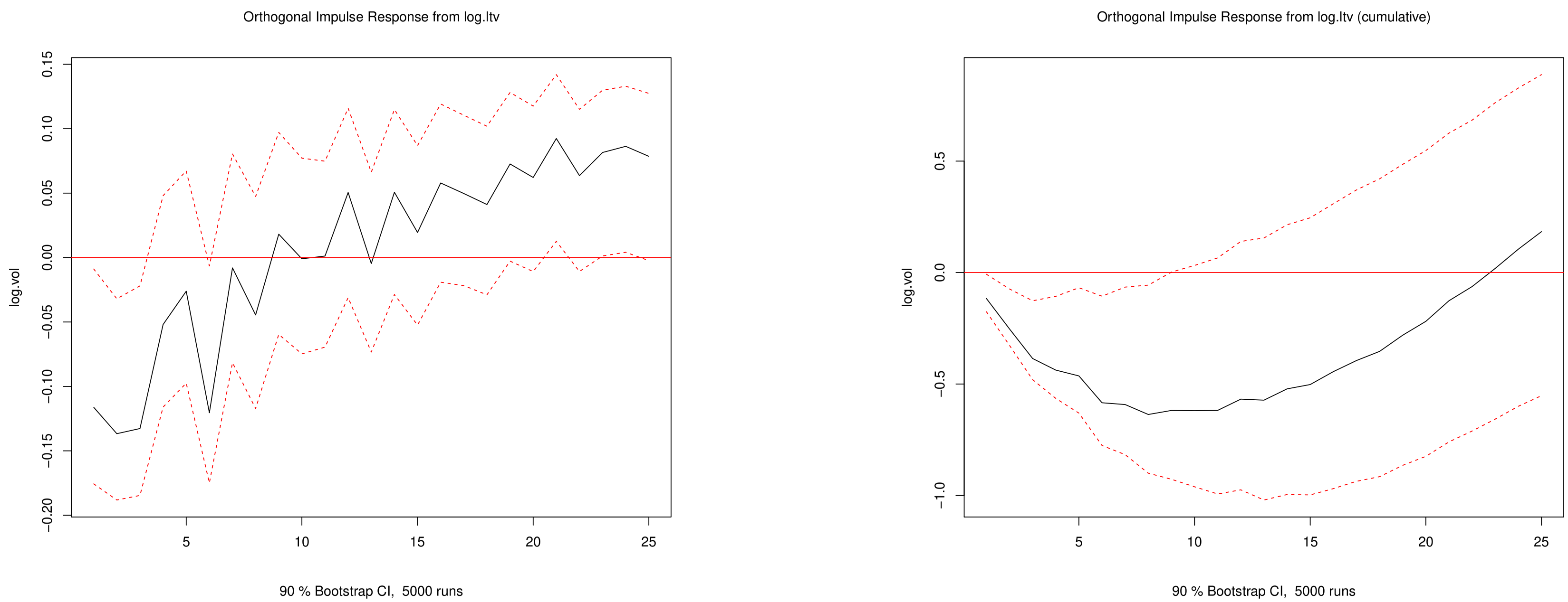

Figure 14: Impulse-Response Function, $log.ltv$ on $log.vol$, Core Open-Ended Funds Only.

This figure shows an orthogonal impulse-response function of *log.ltv* on *log.vol*, with the left panel showing the marginal impulse-response function, and the right showing the cumulative. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), and *log.vol* (the trading volume). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

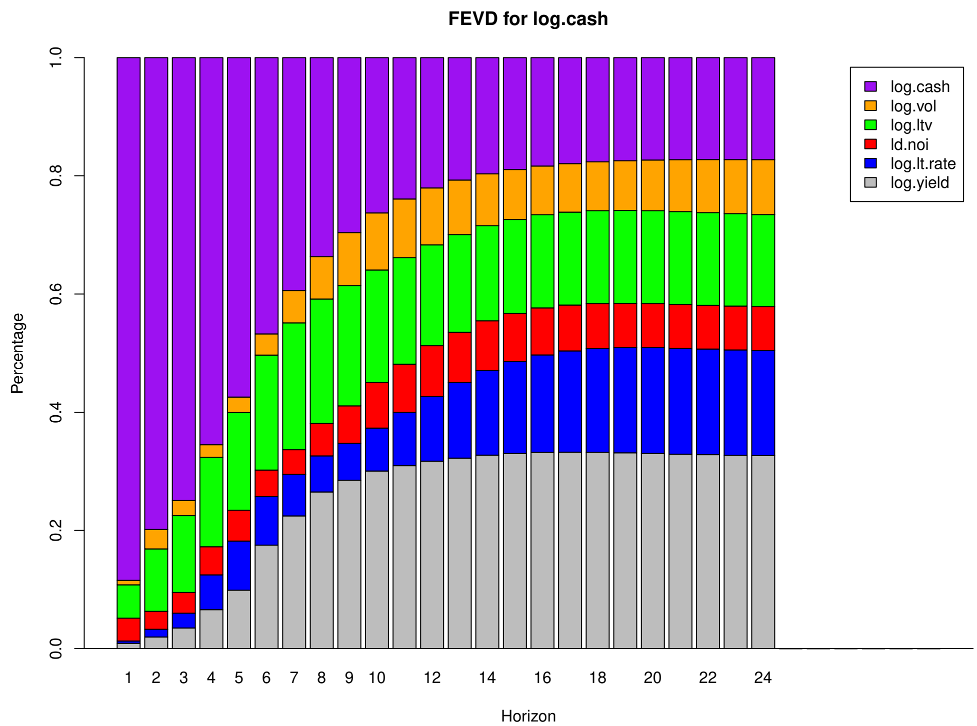

Figure 15: Forecast-Error Variance Decomposition for *log.cash*, Core Open-Ended Funds Only.
This figure shows the forecast-error variance decomposition for *log.cash* from the VAR estimated over state variables aggregated over the properties held by Core Open-Ended Funds. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), *log.vol* (the trading volume), and *log.cash* (the fraction of fund assets consisting of cash). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. Due to the shortened time period, this VAR system uses only 4 lags.

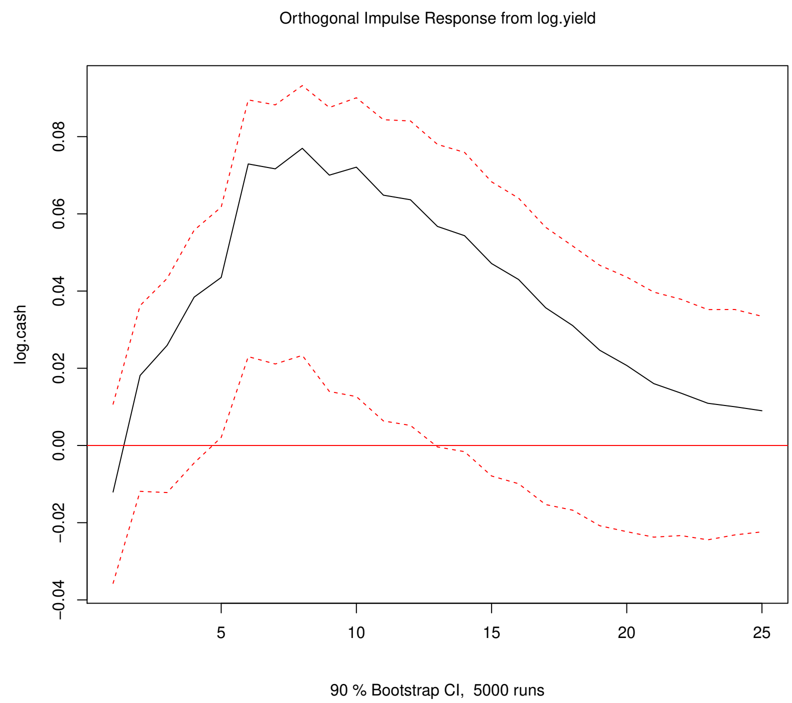

Figure 16: Impulse-Response Function, *log.yield* on *log.cash*, Core Open-Ended Funds Only.
This figure shows an orthogonal impulse-response function of *log.yield* on *log.cash*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), *log.vol* (the trading volume), and *log.cash* (the fraction of fund assets consisting of cash). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. Due to the shortened time period, this VAR system uses only 4 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.

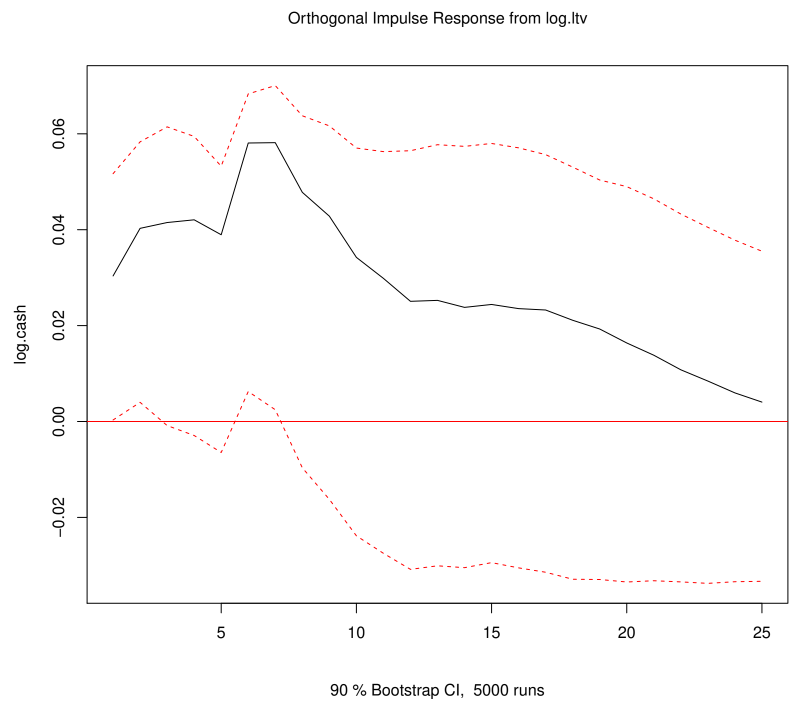

Figure 17: Impulse-Response Function, *log.ltv* on *log.cash*, Core Open-Ended Funds Only.

This figure shows an orthogonal impulse-response function of *log.ltv* on *log.cash*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), *log.vol* (the trading volume), and *log.cash* (the fraction of fund assets consisting of cash). For this sample, *log.ltv* is the same state variable as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate remains the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. Due to the shortened time period, this VAR system uses only 4 lags. 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.