Leverage Cycles in a Mature Asset Class: New Evidence from Commercial Property Markets *

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Abstract

Unifying significant elements in real estate finance, we use the Bernanke-Gertler framework to model leverage cycles in US commercial real estate. We model capital-market yields, as conditioned by market-wide leverage, an indicator of debt availability, and jointly model investment, leverage, debt terms, and the aggregate appetite for risk. Our VAR framework delivers variance decompositions and impulse-response functions which show that leverage and its investment-related effect 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 investors in commercial real estate.

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1 Introduction

Levered investment is a cornerstone of the commercial real estate (CRE) market, and this depends critically on the supply of leverage. But how important a driver of CRE prices is debt availability, relative to other important factors that drive prices in this market? A careful answer to this question depends on constructing an empirical framework, which models the economic mechanism behind the interplay of these two variables. This is a complex one: a feedback cycle exists, in that, in collateralized lending, asset values drive the availability of debt, but debt availability drives asset values. In addition, numerous other variables, such as cash flows, investment, risk appetite, and even the risk-free rate should play a role in driving both asset prices and debt availability. To complicate matters, different investors use different amounts of leverage. Are the asset prices of these different investors differently affected by debt availability? If so, does this create a segmented asset market, with capital flows between the two segments, based on the state of debt supply? This complex interplay of factors has made answering these questions very difficult. In this paper, we adopt a classic macroeconomic framework to shape our thinking about these questions.

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. The effect of the reduced investment is two-fold. First, it causes a decline in real output. Second, it causes a broad decline in the values of those assets for which investors lever up, and through knock-on effects for all asset values, which, in turn, exacerbates debt constraints. 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)). Commercial Real Estate (CRE) can be thought of as a microcosm of a production economy, whose product consists of *space*. Consistent with this, the Bernanke-Gertler (BG) cycle offers a ready-made framework within which to model the effects of debt availability and account for feedback and the interplay of other economic factors.

We contribute to the literature by establishing the Bernanke-Gertler mechanism of collateral constraints as the primary driver for debt availability in Commercial Real Estate, and quantifying its relative importance as a source of asset-price variation in this market. In line with the BG mechanism we present evidence for the central role of investment as a mechanism in driving the effects of debt constraints on asset prices. We find that credit supply constitutes the single most important source of innovations in CRE yields, and that investment constitutes the primary channel through which debt availability drives asset prices. In establishing the link between the effects of debt availability and investments we unify two important strands of the CRE literature, which have thus far treated these two subjects separately. Doing so should enhance our understanding of the mechanisms at play in this context.

The mechanism described in the Bernanke-Gertler cycle is intuitively appealing. However, even in macro-economics, modeling this mechanism empirically and determining its relative economic magnitude as well as its importance for asset markets, has so far proven difficult. Our study solves many of these past modeling problems.

Generally, it has been difficult to measure the relative importance of the Bernanke-Gertler mechanism compared to alternatives. For example, output-related effects (rather than effects related to the value of collateralizable assets) could be driving credit availability. Bernanke, Gertler and Gilchrist (1996), for example, remark that "a finding that credit leads output can be generated by a model in which credit responds passively to expected production and in which there are no important credit-market imperfections; see, e.g., King and Plosser (1984))." Further, while prevailing theory emphasizes the collateral constraint, ability to pay may also matter, as inability to service debt may also trigger default; debt may therefore be scarce if projects cannot meet required cash flows, even though collateral value is sufficient. In other words, the entrepreneur's income statement may be as much of a source of debt scarcity as her balance sheet. Beyond this, simple risk appetite unrelated to collateral values might drive willingness to lend in an economy. In CRE, as well, all these alternative factors could be important drivers of debt availability.

In the CRE setting, we can overcome past difficulties encountered in modeling this mechanism. These 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 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.

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. In CRE, we have the advantage of being able to measure asset yields, since we can observe cash flows to assets in this market, in addition to valuations. 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. Within this framework, debt availability becomes a driver of the discount-rate portion of the yield. This approach addresses the identification problems that are often found in this type of analysis. In CRE, we also have *time-to-build* effects, which eliminate contemporaneous movements in the state variables (a common problem of reduced-form VAR analysis), and can thus eliminate ambiguities in interpretation of results that might otherwise arise in such a modeling framework. Further, by examining yields, we separate asset-value (i.e. price) and output (i.e. cash-flow) effects.

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 particularly slow. However, there should not be anything about leverage cycles that makes these phenomena particular to emerging asset classes: we should also find these in mature asset classes. CRE constitutes a mature and important asset class, in which we are still able to model Bernanke-Gertler debt cycles, because the CRE 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.[1]

The CRE setting, besides allowing the modeling of the BG cycle itself, also allows us to rule out prominent alternative mechanisms mentioned above, that could be driving debt-induced asset-price cycles. Since we can observe cash flows from the properties, as well as cash flows to debt, we can measure effects of output, as well as ability-to-pay constraints, on credit availability. These drivers can be horse-raced these against the balance-sheet constraints, which drive the BG mechanism. The BG mechanism thus provides the empirical framework by which we can establish the relative importance of collateral-driven debt constraints to CRE asset prices; conversely, in the CRE setting we have the unique advantage of being fully able to model its salient features, and rule out prominent alternatives.

There are further advantages to the CRE setting in modeling leverage cycles. Many CRE investors use leverage, at a level comparable to that of the US economy, and any scarcity of debt therefore makes it similarly difficult for those agents to invest, as it would in a macro context.[2] In

[1] 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.

[2] The leverage in this segment of the CRE market is only slightly lower than the leverage of US corporations implied by the *Total Debt to Equity for United States* reported by the St. Louis Federal Reserve.

this sense, we have a natural laboratory in which to test the Bernanke-Gertler mechanism itself, in a macro-economics context. In contrast, some investor groups use little to no debt. We can disentangle two competing hypotheses with regards to these latter investors: this group could suffer losses due to declining asset values (or liquidity), just like low-leverage entrepreneurs in the BG setting. Alternatively, these investors could be able to make profits by being the buyer of last resort for levered investors who need to sell. 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. We can distinguish among riskier and less risky investments to test a lead-lag relationship in deleveraging as the debt cycle sets in.

Our study's methodology thus consists of modeling debt cycles by tracking CRE yields (*cap rates*), through the dynamic Gordon-Growth Model setting of the Campbell-Shiller VAR, the standard methodology for modeling this quantity. Our primary variable used in modeling balance-sheet constraint driven 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.[3]

We thus augment the Campbell-Shiller VAR by adding state variables for leverage (through LTV), investment, a modified debt-service coverage ratio (DSCR), and risk appetite, to model the discount-factor portion of yields.[4] We use data from the National Council of Real Estate Investment Fiduciaries (NCREIF) for our investigation.[5]

Having estimated our VAR, we examine forecast-error variance decompositions and impulse-response functions. We find that credit effects jointly constitute the largest driver of innovations in yield at shorter time periods, with LTV accounting for two-thirds of this variation, and modified DSCR one third. At longer time horizons investment dominates yield innovations, although credit effects still explain about three quarters of the variance of the investment shocks. Further, our analysis shows that investment itself is driven by LTV (and to some extent modified DSCR), a result that is in line with predictions of the BG framework, in which reduced investment is one of the most important channels, through which credit constraints feed back into asset values in the longer term. In comparison to other variables, the magnitude of credit effects on the yield exceeds those of the risk-free rate, and by far exceeds those of risk appetite and output.

In line with the BG framework, yield is the dominant driver of innovations in LTV at short time horizons. At medium time horizons, risk appetite takes this position, indicating that, after the

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

[4]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.

[5]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.

initial asset-value based shock to credit, as the debt cycle deepens, a reduction in debt availability through tightened lending standards is contemporaneous with an economy-wide reduction in risk appetite. At long time horizons, investment takes over as the primary driver of LTV, indicating that, as the cycle deepens, levered investment becomes less feasible and deteriorating collateral further reduces lenders' willingness to lend. We are further able to trace the leverage cycle through its remaining steps, which occur due to debt scarcity; as discussed above, the first effect is reduced investment. As mentioned, the effect of this reduction in investment feeds back into yields, thereby reducing asset values and deepening the leverage cycle. We are also able to trace the second effect of the reduced investment into reduced output (which we measure as cash-flow growth).

We further examine the dynamics of modified DSCR, and find that ability-to-pay constraints do not act like balance-sheet constraints in this setting: these do not significantly drive either yield or investment in a way that would be consistent with debt scarcity existing in this dimension. Further, we find no type of link between ability-to-pay constraints and balance-sheet constraints, that would indicate that these two types of lending constraints either complement or offset each other. Additionally, we do not find that output is a significant driver of debt availability, in that LTV is not driven by our output variable. The combined evidence around both these cash flow variables thus rules out the hypothesis that credit responds to predicted output.

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-Gateway* versus *Gateway* markets respectively. We find that *Non-Gateway* markets lead *Gateway* 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 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 BG 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 by being buyers of last resort 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 act as buyers of last resort. Consistent with this, we examine cash holdings of ODCE funds, and show evidence that these entities hoard cash at the beginning of downturns, likely to retain the ability to meet future redemption requests. To our knowledge, the dynamics of ODCE cash holdings have not been examined in the literature to date. Thus, as in the BG model, low-leverage entrepreneurs are still unable to invest profitably in a downturn.

In the BG 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.

Two existing branches of the CRE literature have separately examined the two sides of this problem. One the one side, Ambrose, Benjamin and Chinloy (1996, 2003) develop a detailed model of debt markets (both the supply- and demand side), and Arsenault, Clayton and Peng (2013) examine the feedback loop between cap rates and mortgage supply. However, for the full Bernanke-Gertler mechanism, investment is the key driver behind the observed interplay. Separately and without specific regard to debt supply, CRE investment has been studied by Ghosh and Petrova (2017), and Ambrose and Steiner (2019). Our approach in this paper, grounded in the Bernanke-Gertler framework, ties these two parts of the literature together. Earlier findings that capital expenditures decrease in times of economic uncertainty or market volatility are consistent with our empirical findings. Importantly, we establish a lack of credit availability during these episodes as a contemporaneously associated effect, and possibly an additional driver of such results.[6]

The rest of the study proceeds as follows. Section 2 reviews further literature and presents our economic framework; Section 3 presents methodology and data; Section 4 presents our results; Section 5 concludes.

2 The Economic Framework

2.1 Literature Review

Our study makes a contribution to the CRE literature, but also to the debt-cycles literature in macroeconomics. In this section we place our study within each of these two fields.

We have already pointed to some relevant CRE literature in Section 1. Additionally, of special note here is the study by Ling, Naranjo and Scheick (2016) which resembles ours in spirit, in that the authors also use a VAR framework to examine the feedback cycle that exists between debt availability and asset prices in CRE. Importantly, however, the authors focus on liquidity in their study, and examine prices directly. Their conceptual framework resides more in the intermediary asset pricing paradigm. In our study we are able to add a deeper understanding of the issues explored in this earlier study, as we move to the original Bernanke-Gertler framework, and establish investment as the primary channel through which this feedback cycle takes place. Further, by examining yield we are able to separate capital-market effects from potential output-driven effects and thus directly decompose the discount factor. We also separate the different roles of aggregate risk appetite and balance-sheet constraints in driving credit supply.

[6]The optionality of CapEx discussed in Ambrose and Steiner (2019) is also in line with our results: underlying volatility makes the deferral (call) option of CapEx more valuable. At the same time, it makes the embedded put option in debt more valuable, and therefore makes debt more expensive and scarce. The debt availability as driver of investment is therefore a flip side of the optionality of investment itself.

In a related study, Duca and Ling (2020) explore the link between cap rates and overall changes in capital supply, versus changes in the required rate of return. The authors use survey data to disentangle these two sources of variation. Our approach differs conceptually and is therefore able to add a different perspective to our understanding of the price formation process in CRE: by working within the Campbell-Shiller framework, we actually decompose the ex-post realized discount rate itself. We can then make relative attributions to the debt-constraint and investments channel, versus the risk appetite as a driver. Within the debt constraint channel we can further subdivide between balance-sheet driven debt constraints and ability-to-pay constraints, finding a dominant role for the former.

We have already summarized in Section 1 how we tie together the previously separate literature strands of debt availability and investment. Of further note in the investments literature is the study by Peng and Thibodeau (2020) that explores the relationship between cost of debt and investment, and provides evidence on the backward-bending relationship between investment and the interest rate. In the debt availability literature, Titman, Tompaidis and Tsyplakov (2005) find evidence that LTV choice is endogenous and driven by the risk characteristics of the underlying property. The deleveraging patterns we show in our flight-to-quality results are very much in line with this idea. Black, Krainer and Nichols (2017) document the institutional landscape for lending, with the market niche for balance-sheet lenders built around loans that may potentially encounter distress and need renegotiation.

The BG mechanism plays a central role in many macroeconomic models, but studies in this discipline have found it difficult to quantify precisely its relative importance. We now summarize the literature in this discipline and how our approach relates to this.

The macroeconomics literature has argued extensively that the BG mechanism has important real economic effects, a link which we also model in our study. 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 BG 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 BG 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 importance of the BG mechanism itself.

In CRE, as in BG and Fostel and Geanakoplos (2008), 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 BG model. 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.[7] The latter is only accomplished through proxies. In our 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; CRE, on the other hand is strictly an investment with no consumption component. The primary channel through which leverage in the housing market drives real outcomes is consumption, as a function of the consumer's ability to borrow. In our CRE setting, on the other hand, the primary channel through which leverage affects asset values and real outcomes is investment, as a function of entrepreneurs' ability to obtain leverage. This keeps our setting closer to the Bernanke and Gertler (1989) model.[8] Second, in CRE 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.

Lastly, some studies have argued that CRE itself has an impact on real economic outcomes, usually through a channel that affects corporate investment (see e.g. Chaney et al. (2012), Gan (2007)). In contrast, our study examines the leverage cycle in the CRE market itself, as a natural laboratory in which we can model this phenomenon. Besides the insights that this natural laboratory offers us, the close link between CRE asset prices and real economic outcomes further highlights the importance of this setting.

[7] 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).

[8] 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) investigate 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.

2.2 Salient Features of the CRE Landscape

In this section we highlight the features of the CRE landscape which are useful to frame the understanding of the underlying mechanisms within the context of the Bernanke-Gertler paradigm.

The CRE landscape should be thought of as a microcosm for a production economy, whose product consists of various types of *space*. Importantly, space should be understood (as in many urban-economics contexts) as a flow, rather than a stock (e.g. available square-footage per year, as opposed to physical square footage). Subsequently, the *entrepreneurs* in the Bernanke-Gertler sense are landlords.

Development (which expands the stock) or improvement of properties (which expands the useable stock in a particular property class) then becomes an investment into the landlord's ability to produce space, rather than a production of space in itself. This becomes one possible way in which the entrepreneur can conduct investment; the other way is through the purchase of existing buildings. In both cases, landlords invest in their ability to produce space, and so investment can consist of either of these, and therefore becomes the sum of these activities.

Again, in line with the idea of the Bernanke-Gertler entrepreneur, investors buy and sell properties based on purely financial decisions, (risk-return tradeoffs) just like any other financial asset that aids economic production.[9] As is well known, CRE has a high debt capacity, and so the 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 the BG framework is well suited for modeling the effects of debt availability in CRE, and conversely why CRE is a well-suited natural laboratory to model the BG debt cycle.[10]

As is well known, 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] This distinction will become important when modeling *flight to quality* in a downturn in the BG world. At such times we should see capital moving towards *gateway* markets.[12]

[9]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. 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.

[10]While the BG framework deals with entrepreneurs directly, in CRE we have delegated investment managers. This should not change any of the mechanisms behind the model: as long as managers are seeking maximum leverage, and they have external leverage constraints imposed on them by the balance sheets of their assets under management, the reasoning behind the BG paradigm applies.

[11]For examples of *gateway* and *non-gateway* markets, see Table 1. In recent work this distinction is treated explicitly in Ghent (2021).

[12]In the BG paradigm, *flight to quality* refers to capital moving to lower-risk projects in a downturn, and this is how

Our data focuses on CRE private-equity funds (albeit with a very small number of REITs in the sample as well). These 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. As is known, 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 CRE (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: in fact these funds' leverage is limited both by charter as well as by investor expectations. We will use these funds to investigate how low-leverage entrepreneurs are affected by the leverage cycle. Due to their open-ended nature, these funds will face continuous contributions and redemptions. They use *redemption queues* and cash reserves as tools, to manage this flow pressure vis-a-vis their illiquid CRE asset base.

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. 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 BG world.

The ODCE universe consists of 36 funds that pursue a diversified core investment strategy, primarily through private equity real estate investing; the data for these funds begins in the later 1970s. To be identified as an ODCE fund, 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). [13] 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

we treat this concept in our study. Note that in other contexts this phrase may have slightly different connotations. See e.g. Presbitero, Udell and Zazzaro (2014), who study bank lending changes in a credit crunch. In their work and related papers, *flight to quality* is synonymous with home bias where multi-branch banks tend to concentrate their lending in locations closer to headquarters.

[13]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.

limited to, (pre)development/redevelopment or initial leasing/lease-up cycles.[14] Finally, and very importantly for our purposes, the fund may use no more than 40% leverage.[15] These funds quite typically use substantially less than this upper limit, and some funds have zero leverage.

As stated before, ODCE funds hold cash so as to satisfy smaller redemptions in a timely manner. In our analysis of these funds we will use these cash holdings to determine likely contribution- or redemption pressures on the fund. Cash holdings are reported to NCREIF by each fund, and we use these directly in our analysis.

In contrast to ODCE funds, 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 and/or 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 include a broader array of property types in the underlying investments.

As is known, 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 hold loans directly on their balance sheets.

Very importantly for our setting, in most cases, the capital market for CRE debt is segmented from other debt markets, at least in the short term, and we assume this to be the case. This seems plausible: for a bank, for example, there are typically maximum exposures to CRE risk (similar to position limits on a trading desk) that an institution is willing to take, or are permitted by the lender's risk management policies. In other words, bank balance sheets are segmented.[16] 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.[17] In a declining market, when effective

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

[15] 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."

[16] 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. In further evidence, 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.

[17] Ambrose et al. (1996) argue that lenders set underwriting standards and interest rates to maximize profits. Adverse selection as interest rates rise limits the ability of lenders to use interest rates to ration loans, so LTV and

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 BG 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.[18] 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.

Conceptually, the mechanism is similar 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.[19] 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.[20] We therefore use this measure throughout our study.[21]

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 an otherwise distressed debt market. Nevertheless, direct lending by private equity funds remains small enough that the effects associated with the BG debt cycle remain in place.[22] [23]

2.3 Hypothesis Development

We now establish the explicit linkage between the Bernanke-Gertler setting and the debt cycle in CRE. This then leads to the development of our specific hypotheses.

DSCR are used to limit borrower demand for leverage. This is also in line with the results of Fostel and Geanakoplos (2008).

[18]Sagi (2021), for example, finds that outright distressed sales of properties are very rare in the NCREIF universe.

[19]To our knowledge this has not been examined empirically in the literature thus far.

[20]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.

[21]In the private-equity space, debt is largely property-specific. Unlike REITs, these funds do not tend to take on debt separately as an entity.

[22]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.

[23]There may also be some anecdotal evidence that in extreme credit-market downturns, such as after the financial crisis, CRE lending may have been hindered by financial institutions' overall balance-sheet status. To our knowledge, this has not been systematically examined in the literature. However, if this is the case, then in such a situation, our results establish a lower bound for the effect of asset-value driven credit constraints.

As in Bernanke and Gertler (1989), the balance sheets of entrepreneurs are central to the story. 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. 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.[24] As in the BG model, the debt cycle is set in motion by a negative shock to collateral values, or, in this case, property prices. As in the BG 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 BG framework, this makes it more difficult for entrepreneurs to invest (i.e. for potential investors to buy commercial property) since they cannot obtain leverage.[25] 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 BG model, as the downturn continues, we see a *flight to quality*: namely, only lower-risk but also less productive projects are undertaken. In CRE, this should manifest through capital fleeing to *gateway* or *core* markets (the largest geographic areas), with secondary markets therefore leading the downturn. We can measure this in our setting.

Much of this corresponds to general intuition held by practitioners: in a down-cycle, required rates of return rise, cap rates rise, use of leverage decreases, transaction volume dries up, and capital flees funds, either through redemptions or inability to raise new funds. On the other hand, there will be deals looking for capital, so capital placement, where possible, becomes easy.

Once the market turns around, as in the BG model, we should see the opposite set of effects, which accelerate the upturn. As property values recover, LTVs fall, lenders' willingness to lend increases, and investors obtain leverage more easily. This raises investment demand and liquidity, and further raises asset prices, raising LTVs. As the cycle continues upward, lending standards loosen, making debt even more available, including for riskier projects, and higher leverage.

This, too corresponds to intuition held by practitioners: as an up-cycle progresses capital pushes into markets, lowering required rates of return and cap rates, speeding up volume (i.e. deal flow), increasing leverage, moving return seekers to more risky projects, and generally making it more

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

[25]As mentioned above, there could be some lenders who 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.

difficult to place capital, vis a vis the competition.

For the entrepreneurs 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.[26]

The other type of price decline one could see in the CRE market could be caused by falling cash flow (i.e. rental payments).[27] 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. Therefore, for the purposes of modeling the BG 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.[28]

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 model both yields and total prices simultaneously. 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. Initially, this causes a deterioration of space quality, and therefore a reduction in rental cash flows. As the investment problem worsens, a lack of availability of space for economic production will ensue. All else equal, at this point the scarcity of space actually causes an *increase* in rents.[29] This would then

[26]This account makes clear that property investment lending is procyclical.

[27]This highlights the classic distinction we make in real estate 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.

[28]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.

[29]See DiPasquale and Wheaton (1992).

actually begin to cause the market turnaround, as the increase in rents would raise asset prices.[30] We do not model this part of the cycle explicitly, but leave this to further research.

As stated before, in our setting we also have a set of no- or low-leverage investors, in the form of our ODCE funds. In the BG 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, is that these funds, operating without the 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.

3 Empirical Methodology and Data

3.1 Empirical Methodology

Our empirical methodology centers on modeling cash-flow yields. In financial asset pricing, one of the most suitable methodological frameworks for empirical modeling of capital-market yields is the Campbell-Shiller Vector Autoregression (VAR) (see Shiller (1992)). This framework characterizes the asset market's price formation process empirically, and therefore allows a decomposition of the variance drivers in asset markets.[31] Further, the BG model describes a feedback cycle, in which declining asset prices affect leverage, and declining leverage affects asset pricing. A VAR model is an appropriate empirical tool for capturing 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

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

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):[32]

[30] 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.

[31] Accurate variance decomposition of the yield lie at the heart of our results, and so doing this carefully is important.

[32] Equation 1 contains, in addition to these variables, the parameter ρ which constitutes the long-term expected return of assets. In addition, since the Campbell-Shiller model is a log-linearization the model is only defined up to a constant, C.

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

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 BG framework in a commercial real estate setting is that changes in property value (due to changes in yield here) are a function of changes in *entrepreneurial net worth*, i.e. the asset value relative to debt balances, or loan-to-value (LTV). [33] In the BG framework, once debt becomes scarce, liquidity of the market is adversely affected, which in turn further depresses asset prices. In a larger sense, however, the market liquidity channel is part of a broader investment channel, which dries up and depresses entrepreneurs' asset values. Liquidity in the CRE market can be measured by transaction volume.

In a larger context, however, market transactions (i.e. buying buildings) actually only constitute one way for entrepreneurs to conduct investment into new projects. The other way for entrepreneurs to invest is by improving existing buildings through Capital Expenditures (CapEx). Therefore, we construct an investment variable (inv) which combines both of these aspects of CRE investment. It is defined as signed net volume (purchases minus sales) plus capital expenditures, all scaled by total portfolio value. With this variable, we thus capture entrepreneurs' investment behavior in the BG cycle. Investment behavior should then also be the primary mechanism by which credit-market effects carry through to output (which in our setting is then captured by NOI growth, Δd). Further, investment will also directly affect asset prices, since CapEx affects the quality of buildings, and trading behavior affects prices (through a traditional liquidity channel). This is one channel in the feedback mechanism of the BG cycle. We thus augment the Campbell-Shiller VAR by adding as discount-factor variables aggregate LTV and investment, both in logs.

LTV (or a collateral constraint) is only one way in which lending constraints could bind in this world. The other way in which this could happen is through a cash-flow (or ability-to-pay) constraint. In the CRE world this concept is generally referred to as Debt Service Coverage Ratio (DSCR) for a loan. Besides LTV, this is the other major indicator of the safety of a loan, and the other important constraint often imposed by lenders and secondary markets, such as CMBS. LTV is a constraint on the entrepreneur's balance sheet, while DSCR is a constraint on the entrepreneur's

[33] 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.

income statement. For computational reasons (see Section 3.3) directly adding DSCR to our model is not feasible. Instead, we capture this factor by constructing a variable ($NmDebt$) that measures the difference between NOI and debt payments and therefore shows ability to pay. We thus compare the effects of collateral- and ability-to-pay based lending constraints, and *horse race* them against each other empirically.

Lastly, the discount factor in the capital market is likely also driven by the aggregate risk appetite in the economy. If any of our credit variables are correlated with this, we could make inadvertent attributions to credit effects, thus overstating their importance. To capture such effects directly, we include the *pvs* measure proposed by Pflueger, Siriwardane and Sunderam (2020) as an additional state variable in the VAR. The intuition of their measure is that the valuations of high volatility (vs. low volatility) stocks vary systematically over the business cycle with variations in risk appetite. *pvs* is the difference between the average book-to-market ratio of stocks in the lowest return volatility quintile and the average book-to-market ratio of stocks in the highest return volatility quintile. When market valuations are high, book-to-market ratios are low, so *pvs* is high when the price of high-volatility stocks is high relative to low volatility stocks.

If the BG mechanism is operating in the CRE market, our empirical 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 (at least initially), a change in the building yield changes the building value and therefore LTV. However, in addition to this, we should see a tightening of lending standards once the downward debt cycle sets in, and this should depress LTVs beyond the initial mechanical variation due to changing yields.[34] LTV should then drive investment, since reduced debt availability makes purchases of buildings, as well as improvements to buildings (for both of which entrepreneurs obtain loans) less feasible.[35] Lastly, investment should drive yields, as market liquidity determines prices to some extent, and the degree of CapEx affects the quality of the buildings. This completes the BG feedback cycle. While our study is primarily concerned with the capital-market dimensions of the BG mechanism, we can also investigate its linkage to output, by observing whether investment drives NOI growth in this setting.

Our modeling framework also constitutes an ideal setting to test the alternative hypothesis that credit responds passively to expected output, rather than being driven by asset values. The premise of the Campbell-Shiller VAR is that each state variable with its lag structure captures current market information in such a way that predictions from this VAR proxy for market predictions. Thus, if credit availability responds to expected output, we should see our output variable (Δ_d) drive LTV (and possibly $NmDebt$).

The full VAR model then becomes:

[34] The mechanism by which this tightening of lending standards manifests will be in new loans issued with lower LTVs. Therefore the adjustment of portfolio-wide LTVs should be gradual.

[35] This reflects the common assumption in the literature that debt is required to finance investment. We show in Section 4.4 that even low-leverage investors who might rely on cash reserves to finance investment may not have cash available to pay for buildings or building improvements in a downturn.

$$[LTV_t, inv_t, NmDebt_t, pvs_t, \delta_t, r_t, \Delta d_t]' \tag{3}$$

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.[36] All variables are aggregated across the NCREIF portfolio as value-weighted averages or sums, respectively, except for the two macro variables (r and pvs), which enter directly.

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 (1996) 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 Contemporaneous Relationships

The Campbell-Shiller VAR constitutes the accepted framework for modeling capital-market yields. However, the framework is a reduced-form model; with the possible presence of contemporaneous shocks to the state variables, the impulse-response functions may not yield unambiguous interpretations in such a setting. In our model, however, our results are not subject to such concerns. We explain this below.

We begin by noting that the reduced-form model which we estimate (Equation 3) is actually a restricted version of a system consisting of the following primitives: Property cash flow (NOI); Entrepreneurs' Debt Balance ($Debt$); Net Space Acquisitions in the Market ($NetBuy$); Capital Expenditures ($CapEx$); Entrepreneurs' Debt Payments ($DebtPmt$); Entrepreneurs' Risk Premium (rp_e); Entrepreneurs' Expected Cash-Flow Growth (g_e); Risk-free Rate (r); Risk Appetite (pvs); Appraisers' Risk Premium (rp_a); Appraisers' Expected Cash-Flow Growth (g_a).

We note first that property prices are not true primitives, but rather are constructed, by the Gordon Growth Model, as $p = NOI/(r + rp_e - g_e)$. rp_e and g_e are unobservable latent variables.[37] Note similarly, that appraisal values as such are not true primitives, but rather follow from the appraiser's application of the Gordon Growth Model, but using subjective estimates of the parameters. In other words, appraisal values are defined as $a = NOI/(r + rp_a - g_a)$.

Recognizing this, the reduced-form model we estimate, then becomes a restricted version of a

[36] See Subsection 3.3 for more specifics on how all state variables are computed.

[37] The Campbell-Shiller VAR framework is designed precisely around this recognition, as a tool to infer these two quantities. In our exercise, the key quantity for the BG cycle is rp_e, and so we use the Campbell-Shiller methodology to model this.

system of the above primitives, involving a set of cross-equation restrictions. In terms of these primitives, the variables in our reduced-form model are defined as follows:

$$\begin{aligned} LTV &= \frac{Debt}{a} = \frac{Debt}{NOI/(r + rp_a - g_a)} && (4) \\ inv &= NetBuy + CapEx && (5) \\ NmDebt &= NOI - DebtPmt && (6) \\ \delta &= \frac{NOI}{p} = r + rp_e - g_e && (7) \end{aligned}$$

Δ_d is nothing but a restriction on the lag structure of NOI (since it is defined as $NOI_t - NOI_{t-1}$). pvs and r enter unrestricted. Our Campbell-Shiller based model thus involves nothing but a set of (in part complex and non-linear) cross-equation restrictions on a system involving these primitives. The fact that we use logs of all variables should even make these restrictions linear, although this is not strictly necessary.

A concern may exist whether vis-a-vis the need for capital improvements to a property, pure NOI is actually the right measure for cash flow. This would influence both our definition of the yield, as well as our ability-to-pay variable. The definition of the yield is based on the Gordon Growth Model; this implies a constant-growth perpetuity of cash flows. One-time capital expenditures, such as renovations are deliberately omitted, as they do not affect the value over an infinite horizon. In our model, these are part of investment. More frequent capital expenditures (such as remodeling of apartments in between tenants) are budgeted for through a CapEx reserve, which in the proforma of that property converts this irregular expense to a regular one, that is now included in NOI. With regards to ability-to-pay, the latter point also applies. With regards to large renovation expenses, such as are involved in the turnaround of a property, these will normally be financed through external sources, and will not affect ability to service current debt. It is difficult to envision, for example, an office building which remodels its lobby, but defaults on current debt in order to do so. Should external capital not be available for the lobby renovation, the lobby renovation would likely be deferred until it can be financed. We model this explicitly by looking at the impact of debt constraints on our investment variable.

We now discuss the potential contemporaneous effects on the set of primitives. In other words, will a shock to one of the primitives cause another primitive to adjust within a quarter? We argue that this will not be the case. To show this, we rely on a *time-to-build* argument; all the primary relationships among primitive state variables in this setting are subject to such a limitation. This manifests in terms of literal time involved in construction, long-term fixed leases, slow transaction time, fixed debt payments with slow refinancing and call protections, and fixed appraisal schedules. We develop these points below.

NOI is based on cash flows derived from long-term leases. Lease terms cannot generally be renegotiated within a quarter, so as to materially affect cash flows within that quarter.[38] Possible exceptions to this could be found in apartments, in which leases are annual but roll over asynchronously, as well as in hotels, in which leases are nightly, so revenues could change quickly. The relevant question in these two sectors, is to what extent NOIs change as a function of the other variables in the system. The only other variable in the system, which could plausibly affect hotel- and apartment NOIs immediately, would be $CapEx$ (like renovations to buildings), since these could potentially improve the quality of the space, which will therefore command higher rents. However, $CapEx$ themselves will have a long lead- and execution time, in part due to permitting, and in part simply due to construction time. Once the renovation is finished, in an apartment building, enough units have to turn over to leases which reflect the improved space quality, in order to raise NOIs substantially. In a hotel which makes substantial renovations, part or all of the property will be shut down during the work; after renovations are complete, the property will only gradually fill back up as the hotel effectively re-enters the market, and nightly rates will be kept low during this time to improve occupancy, thus still not reflecting the improved quality of the space.[39] None of the process described above (i.e. renovating and then re-leasing the property to affect NOI substantially) can be completed within a quarter. Beyond $CapEx$, the two macro variables (r and pvs) could change quickly. However, with these variables, it is unclear that they would have an immediate effect on either apartment- or hotel NOIs.

The other primitives themselves will not change quickly enough to affect NOI, or any other variable in the system within a quarter; similarly they will not allow the response to a shock in another variable to manifest within a quarter. A change in the entrepreneur's debt balance ($Debt$) or debt payment ($DebtPmt$) would require refinancing a mortgage, which is difficult to do within a quarter. Debt balance reductions through pre-payment are also generally not possible on first mortgages, since commercial mortgages are for the most part call protected.[40] Similarly, space acquisitions cannot be made within that time interval: trading a commercial building requires three months at a minimum, but more likely six to nine. This locks in $NetBuy$ within a quarter. Shocks to the latent variables that generate building prices, rp_e and g_e, cannot manifest without building trades, so these are also fixed for the quarter. By a similar argument, the latent variables in appraisals (rp_a and g_a) require re-appraisal of a building for a shock to manifest in these. Intra-quarter reappraisals do not take place. Thus these two variables are also fixed within a quarter. As mentioned earlier, $CapEx$ will also have a long lead- and execution time. Therefore, these will

[38] Operating costs (which could also affect NOI) are also generally set by longer-term contracts. Examples for such costs include ongoing building maintenance, landscaping, or security services.

[39] In addition, hotels tend to time renovations for low seasons and make every attempt to finish renovations in time for the high season. It is not until the high season that the value of the new space will be fully realized in NOI. Note further that hotels only make up less than one percent of the value of the NCREIF portfolio. Lastly, hotels owned by core funds would not undergo substantial CapEx; this would only happen for value-added investments.

[40] An exception to this could be found in mezzanine debt tranches, which sometimes take the shape of preferred-equity-like securities, or sometimes credit lines. Through these, debt balance changes can be made in the short term, but these tend to be small.

also not happen within a quarter. With regard to the two macro-economic variables, r and pvs, we do not examine responses to these from any impulses to our other variables, so contemporaneous relationships should not cause incorrect interpretation in either case. However, it would likely be reasonable to assume that any shock to a variable in the commercial property market would not be strong enough to have a contemporaneous effect on the full economy's risk-free rate or risk appetite.[41]

Thus, we should not have contemporaneous relationships among this system of primitive state variables. The VAR we estimate is a restricted version of the system of the primitives discussed here, and should therefore also not suffer from interpretation problems stemming from unaccounted-for contemporaneous relationships.

In addition, we impose several explicit restrictions to the VAR system we estimate. We construct these by testing zero restrictions between two state variables (including all lags) that we find economically plausible, in a likelihood ratio test. We impose the subset of restrictions that we cannot reject statistically. Specifically, we restrict to zero the coefficients for all lags of Δ_d and $NmDebt$ in the equation for r, as well as the coefficients for all lags of pvs in both the equation for Δ_d and $NmDebt$. Since we have natural restrictions, as well as additionally-imposed restrictions to our VAR system, we note that (like all restricted VARs) this system cannot be estimated through equation-by-equation OLS. We therefore estimate the full system simultaneously, through feasible GLS.

Unlike for the original Campbell-Shiller VAR, stationarity of state variables in the system (or lack thereof) should not be a concern in this context. Stationarity matters in a VAR context only when performing statistical hypothesis tests on the coefficients. For Campbell and Shiller, stationarity is necessary, as their conclusions center around the Wald test of the Campbell-Shiller restriction, which allows them to reject the dividend-discount model. This requires stationarity, in order for its distributional assumptions to hold. See: Sims (1980), and especially Sims, Stock and Watson (1990). These studies argue that a Wald F has a limiting distribution of Chi-Sq if and only if all regressors are canonical and stationary. For the analysis of FEVDs and IRFs, non-stationarity should not be a problem. All that happens when performing such analysis on non-stationary data is that impulse responses will be permanent, and not decay with time. Bootstrapped confidence bands are then simply put around the permanent response, so inference associated with the IRFs should not be an issue either. In fact, Sims recommends not to manipulate variables so as to eliminate non-stationarity as this can hide true relationships which exist in the data (which might be cointegrating relationships). The general sense from this literature is that if the VAR state variables mimic the true underlying data generation process, the cleanest observation of relationships in the data can be made. (See also Enders (2008).)

[41] Anecdotally, in CRE downturns (such as the Savings-and-Loan Crisis of the late 1980s and early 1990s), we have not seen immediate large macro-economic effects. This is unlike the 2007-2008 financial crisis which was triggered by housing.

3.3 Data

The NCREIF (National Council of Real Estate Investment Fiduciaries) data is the foundation of our empirical work. This is a vast database of US property holdings, and covers the majority of privately-held institutional-grade CRE in the United States. The primary entities reporting data to NCREIF are Commingled Real Estate Funds (CREFs). NCREIF collects this data to construct its National Property Index (NPI) the de-facto standard CRE performance benchmark in the United States. We use this index data, as well as data on individual properties, as reported to NCREIF.[42] [43]

As of the first quarter of 2018, the NPI reflects investment performance for 7,553 commercial properties, totaling \$567 billion of market value. 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; debt payments for each property each quarter; Capital Expenditures for each property in each quarter. We aggregate all data in each quarter on a value-weighted basis, either directly, or by use of an index (see below). Debt balance and appraisal constitute the two elements for our LTV variable.

Due to the scarcity of CRE transactions, performance evaluation in this industry frequently relies on the use of appraisals. It is well documented in the CRE 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 understating return volatility, and therefore makes performance evaluation difficult. The NPI is known to suffer from this problem.

We now discuss the implications of the use of appraisals for our study. In constructing our LTV variable, appraisals are actually desirable. This is because in the BG 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 constructing our LTV variable, we would be mismeasuring lenders' perceived exposure, and therefore debt scarcity.

[42] As academic researchers, we are given access to NCREIF's raw data under a non-disclosure agreement.
[43] We use the full NPI and all of its member properties for the main portion of our analysis.

To compute 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:

$$y_t \quad = \quad (tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} \tag{8}$$

where *tot.ret* is the total return to the TBI and *app.ret* is the price-appreciation return.[44]

As stated, the NCREIF TBI is a repeat-sales index. To be effective, this 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 to compute a reliable transaction-based index. 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 produce a reliable repeat-sales index. Therefore, for this part of our study we have no choice but to rely on appraisal-based values.

While our results for ODCE funds could, in principle, be affected by this data limitation, several mitigating factors arise in the context of our study. The appraisal-smoothing literature in CRE agrees that smoothing introduces excess autocorrelation in prices, especially at a one-quarter and four-quarter lag (these are referred to in the literature as *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 empirical analysis we use eight lag VAR models), 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, since an overly large fraction of variance is attributed to the own-variable lags. Therefore, the dependencies we find are actually a lower bound for true cross-variable dependency among the state variables in our system. Despite these mitigating factors, we rely on transaction-based yields where they are available.

Throughout our analysis, our cash-flow growth variable is defined as the difference in logs of portfolio-wide Net Operating Income (NOI) per square foot (i.e. total NOI divided by total square footage). In the empirical analysis, we call this *ld.noi*. We construct an investment variable (*inv*), defined as net purchases minus sales, plus capital expenditures (all in Dollar amounts), all divided by total property value. This captures the two ways to invest in this setting, namely, purchasing new buildings or improving them, and with the scaling our measure mimics the I/K measure

[44] We include a derivation of this in the appendix.

common in empirical macro and investment models. For the risk-free rate, we use the longest-term US Treasury yield available at any particular time (mostly 30-year bond rates, and where 30-year bonds were not available, 20-year bond rates), from the St. Louis Fed. The *pvs* variable, which measures risk appetite in the economy is drawn from Pflueger et al. (2020); details on its construction are available in their paper.[45]

Cash-flow based credit constraints are normally measured through Debt-Service Coverage Ratio (DSCR). This is ordinarily defined as NOI divided by debt payments. For stabilized property with a mortgage (and therefore as a forward-looking risk assessment for bankers), this makes sense. As an instantaneous measure, or for a wider range of property, however, the measure is problematic, as it is undefined for properties which do not make debt payments, either because they do not have debt payments scheduled, or because they are entering delinquency. Both would be especially important to detect in our setting. It would also not be appropriate to use the inverse of DSCR, as this measure becomes very large (in absolute terms) on either side of zero, and has a discontinuity at zero. None of these properties seem economically warranted, as a situation in which NOI is a very small amount above debt payment is only very slightly better than a situation in which it is equal to, or slightly less than, the debt payment. Conceptually, no big jumps occur in this region. For this reason, we construct a linear measure consisting of NOI minus debt payment, to measure cash-flow related credit constraints. To account for differences in building size, and/or changes in the size of the NCREIF portfolio, we scale this difference by the square footage of the property. This scaling is consistent with the NOI measure. We call the resultant measure $NmDebt$.[46]

In keeping with the log-linearization of the Campbell-Shiller framework, we use natural logarithms of all quantities. Our sample period extends from the first quarter of 1982 through the end of 2017.

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 varies substantially in our sample. As stated earlier, ODCE funds are quite often equity-only in the early part of the sample, and even later in the sample, they use very little leverage. In any case, ODCE fund charters limit the amount of leverage they can take on.[47] REITs (of which there are few in the sample, though) have the highest leverage (around 60% LTV). There is considerable variety in the leverage of the property owners who fall in between these two extremes. The variety in the sample contributes power to the empirical analysis.[48]

[45] We downloaded this measure from https://www.carolinpflueger.com/.

[46] We also considered scaling by property value. However, property valuation is often highly uncertain outside the realm of stabilized property, in which abnormal but nevertheless important values of $NmDebt$ will occur, which are important to incorporate in our study. Examples of such situations would be distressed property, turnaround property, or development property.

[47] See Section 2.2 for more details.

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

We turn now to characterizing the credit constraint variables that play an important role in our empirical work. While we find the overall mean LTV in NCREIF to be a bit under 20%, conditional on there being leverage on a property, mean LTV is a bit over 43%.[49] 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, and which we plot in Figure 1. This choice should be warranted, in that the variable that drives the BG debt cycle is each individual entrepreneur's balance sheet, not the collective 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 (37%).

Turning to the ability-to-pay measure $NmDebt$, we find the overall time-series mean of this variable is 0.92, meaning NOI per square foot exceeds debt payment per square foot by 92 cents. In one quarter (Q1 of 1993), this measure becomes negative ($\$-0.30$). Otherwise, $NmDebt$ shows considerable volatility within an approximate range of $\$0.20 - \$1.00$ until about 2011, at which point it begins a significant increase that more than doubles its value in seven years. As LTV was falling, $NmDebt$ was rising dramatically. Other than this period at the end of our sample, the two credit measures have no compelling comovement for the previous 30 years of our sample period.

We further characterize the LTV and $NmDebt$ variables from this data through the time-series plot in Figure 1. As the diagram makes clear, leverage rises substantially through to the 2008-2009 financial crisis before retreating through 2015. The increase in LTV beginning in later 2007 undoubtedly reflects the decline in building values at the time, not fundamental delivery of commercial real estate in the NCREIF universe. Some of the early rise in LTV may be traced to the addition of new, levered properties into the NCREIF universe in the 1980s and early 1990s. Nonetheless, the availability of leverage and rising building values in the early 2000s were roughly in proportion. Since 2015, realized LTV has settled about five percentage points lower than the 1995-2005 period.

4 Results

4.1 Variance Decomposition

To assess the evidence for the leverage cycle in our setting, we rely primarily on variance decomposition and impulse response function methods. The variance decomposition indicates 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

Fed policy.

[49] These results are untabulated to save space, but a table is available upon request.

functions can also help to characterize the horizons at which different variables have a major (or minor) impact. The impulse-response functions then show the direction in which this variance manifests. We use eight lags for the full-sample VAR.

Figure 2 graphically shows the forecast error variance decomposition for the log of the property yield and Appendix Table C.1, Panel A, shows this numerically. By examining yield, we establish the relative economic importance of the BG mechanism to the functioning of the asset market.

As both the diagram and the table clearly show, yield shocks have a very large own effect (i.e. persistence is large). From 3 quarters forward, LTV begins to account for a noticeable portion of variance, and accounts for between 9% and 12% of variance at all horizons after this (with higher fractions at longer horizons). The other credit variable ($NmDebt$) also begins to account for noticeable proportions of variance from three quarters forward, accounting generally for around 7% of variance. Collectively then, credit variables account for approximately 18% to 20% of variance over most of the forecast horizons, with two thirds of this driven by LTV and one third driven by $NmDebt$. From 3 to 6 quarters, LTV by itself becomes the largest driver of *innovations* in yield (i.e. variance driver outside the yield's own persistence). Through 8 quarters, the sum of the two credit variables jointly constitute the largest driver in yield innovations.

A variable that becomes prominent over longer horizons is investment. At 6 quarters, this becomes the largest single driver of innovations, and from 8 quarters forward this variable accounts for a larger fraction of variance than the two credit variables together, stabilizing around 27%, while the credit variables together stabilize around 20%. It is noteworthy that investment never supplants the importance of the credit effects, but rather comes at the expense of the yield's persistence. The importance of investment as a driver of yield innovation, especially in the long run, is expected, of course, as investment in buildings (through both the purchase- or liquidity- as well as the renovation channel) drives asset values. The time frame at which this variable gains in importance (about two years) also matches economic intuition, as investment takes time. Much more interesting, we believe, is a comparison, to understand the relative importance of credit effects: at shorter time horizons, the scale of credit effects on yields exceeds investment effects, while at longer time horizons, credit effects remain within the same order of magnitude as investment effects, with the former accounting for about three quarters the variance of the latter.

The *pvs* variable, included in our model to capture the relative importance of risk appetite as a driver of yields, leads to the next interesting comparison. Like most other variables, the effect of this variable becomes noticeable at three quarters. After this, it quickly stabilizes around 6% at all forecast horizons. It is clear that risk appetite should be an important driver of the discount-factor portion of the yield; the interesting observation, here, too, regards relative magnitudes of effects, compared with the credit variables. LTV consistently explains about twice the fraction of variance as risk appetite, while $NmDebt$ explains the same amount. This means, together, credit effects explain three times the amount of variance in yield, that risk appetite does. We find a similar small effect associated with cash-flow growth (*ld.noi*): it tops out below 5% and only reaches this range around 16 quarters. The importance of credit effects on yield exceeds that of cash-flow growth at all horizons, despite the mechanical Gordon-Growth model relationship that makes cash-flow growth a driver of yields.

Of the other variables in the system, the risk-free rate steadily gains in importance with increasing prediction horizon, starting at 5% and ending at 15%. It is no surprise that the risk-free rate is an important driver of yields in an asset market. Instead, again, the comparison to credit effects is important. This shows that, at all horizons, the combined effects of credit on the yield exceed those of the risk-free rate, with pure LTV effects exceeding those of the risk-free rate at low forecast horizons, with the two effects about equal in the medium term, and the risk-free rate exceeding the effects of LTV by about 2 percentage points at long horizons.

In summary, credit effects constitute the largest driver of innovations in yield at shorter time periods; at longer time horizons investment dominates, although credit effects still explain about three quarters of the variance of the investment shocks. Further, as the analysis below shows, investment itself is driven by LTV; in fact, in the BG framework, reduced investment is one of the most important channels, in which credit constraints feed back into asset values in the longer term. In comparison to other variables, the magnitude of credit effects on the yield exceeds those of the risk-free rate, and by far exceeds those of risk appetite. Within the two credit variables, the variance explained by collateral constraints (LTV) is about twice that explained by ability-to-pay constraints ($NmDebt$).

The previous variance decomposition addresses part of our research question, namely, the relative importance of credit effects in CRE asset markets. In the analysis that follows, we examine the evidence for the BG mechanism as the driving factor for the credit effects we observe in the asset market.

We begin with the evolution of LTV. As Figure 2 and Panel B of Appendix Table C.1 makes clear, this variable, too, is highly persistent, with own variation accounting for the largest portion of variance, for all but the 24-quarter horizon. At short horizons we find the largest driver of LTV innovations to be the yield. At one quarter, the yield explains 14% of variance, which declines to 8% and then 6%, at 5 quarters. This is what the BG mechanism predicts: a shock to asset values (and therefore yield) causes LTV to expand initially. From 7 quarters on, pvs takes over as the largest source of innovations, retaining this dominance all the way to 18 quarters; the fraction of variance explained starts at 9%, tops out at 19% at 14 quarters, and then declines a bit to 17% by the end of this segment. During this time, none of the other sources of innovation are nearly as important as pvs, with the yield playing relatively the largest role, with a maximum fraction of variance of 10%. This, too, is evidence of the BG mechanism; the initial mechanical increase in LTV is followed by a tightening of lending standards as the cycle progresses. This comes as part of a general decrease in risk appetite in the economy, making risk appetite the driving factor. At very long horizons, investment becomes the primary driver of innovations in LTV. This is also consistent with the BG mechanism: investment becomes more difficult (or in an upturn becomes easier) as the cycle progresses. The reduced investment in downturns (or the increased investment in upturns) then changes the quality of collateral, and therefore the amount bankers are willing to lend (LTV). As with all investment effects, however, this takes time.

The effect of the other state variables remains small throughout. Of special interest among these is the output variable, $ld.noi$. The fact that this does not constitute an important driver of LTV provides evidence against the hypothesis that credit responds to anticipated changes in output, instead of being driven by balance sheet constraints.[50] The other cash-flow variable, $NmDebt$ also does not constitute an important driver of LTV, as shown here and in the respective IRF (Figure 10).

We next turn to the FEVD for $NmDebt$, the ability-to-pay constraint variable. This variable, too, is highly persistent. As a driver of innovation, $ld.noi$ (NOI growth) establishes itself in the dominant position at a forecast horizon of 3 quarters and continues there through 6 quarters. Throughout the entire forecast horizon, the fraction of variance explained by NOI growth ranges between 7% early, and 16% at medium horizons. Just like between yield and LTV, a mechanical relationship exists between $NmDebt$ and NOI growth, since $NmDebt$ is the difference between NOI and debt payment. Beyond mechanical relationships, though, if a separate debt cycle existed between ability-to-pay constraints as a driver of debt availability, and cash flow growth, as an indicator of output, it would be observable in the relationship between these two variables.[51] The impulse response function will shed more light on whether that is the case.

From 8 quarters forward, the risk-free rate becomes the dominant driver of innovations in $NmDebt$, and in the longer forecast horizons, this is by a wide margin (explaining nearly 40% of variance). The likely explanation for this is that the risk-free rate directly drives debt interest and therefore debt payment.[52] The predominance of this effect as a driver of innovations in $NmDebt$ likely points to simply the absence of other strong drivers for this variable, at longer time horizons. If a debt cycle exists here, its importance does not compare to the importance of these risk-free rate effects. In the latter part of the forecast horizon, investment begins to play an important role, ranging from 10% to 17% of variance after 20 quarters. This should simply come from the fact that investment drives output, and, as in other places, is slow to take effect. Yield remains around 4% of variance throughout, likely due to a mechanical relationship between the two variables, which both contain NOI.

In the first quarter, LTV is actually the dominant source of $NmDebt$ innovations, although its effect is small, at 1.8% of variance. After this, a conspicuously small portion of $NmDebt$ variance is explained by LTV. This suggests that, except in the very short term, bankers do not

[50] The IRF of $ld.noi$ on LTV, not shown to save space, but available from the authors, is also insignificant.

[51] If this were to manifest, the most likely channel for this would again be investment: reduced ability to pay reduces debt availability, which reduces investment. This reduces productivity and therefore NOI, which, in turn, reduces ability to pay and therefore debt availability.

[52] The competing explanation would be that monetary policy drives output. This, however, is countered by the fact that the risk-free rate is not an important driver of NOI growth, our output variable.

trade off balance-sheet constraints against ability-to-pay constraints in determining loan quality or availability. Further, a conspicuously small portion of $NmDebt$ variance is driven by risk appetite (pvs) shocks. This is in stark contrast to the picture for LTV and would indicate that bankers do not use ability-to-pay constraints as a *debt spigot*, the way they seem to use balance-sheet constraints.[53]

The final two state variables are the real-outcome variables of the BG framework. The first of these two is investment, whose FEVD we discuss now. As with all other variables in the model, this variable is highly persistent. At most forecast horizons, LTV is the dominant innovation driver, accounting for around 10% of variation throughout and as much as 14% at the shorter forecast horizons. Adding the effect of $NmDebt$ makes the two credit variables jointly the largest source of innovations in investment, accounting for about 12% of variation throughout. The BG framework predicts that credit availability drives investment, and we find this to be the case. In fact, the credit variables are the primary drivers of investment activity. Yield, pvs, $ld.noi$, and the risk-free rate vary in size of effect, explaining between 5% and 9% of variation each, at various forecast horizons. Each of these effects is plausible, as all of these variables, intuitively, should drive investment. Overall, however, each of these variables explains only half to three quarters as much variation, as the credit-availability variables. Within credit constraints, in this setting, balance sheet constraints take the dominant role by far, explaining three to four times as much variation as ability-to-pay constraints.

The final FEVD we discuss is for $ld.noi$ (i.e. NOI growth), which in our empirical framework proxies for output. This variable, again, is highly persistent and also has two mechanical or at least quasi-mechanical relationships. One of these is the relationship with $NmDebt$, since both variables are based on NOI, and the second is with yield.[54] A non-mechanical relationship, on the other hand, is the one with investment, which accounts for only 3% of variation at short horizons, but as much as 12% at long horizons. This makes its effect of similar magnitude to that of yield, and of higher magnitude than that of the risk-free rate (about twice as large). While links between investment and output (especially at longer horizons) are unsurprising, in our modeling framework this establishes the final linkage of the BG mechanism. Debt availability drives investment, and investment drives output. The effect of LTV itself is small (around 2-3%). This is likely due to the delay with which investment affects output (or, in our case specifically, the previously-discussed delay with which improvements in the quality of space drive increased rental revenues). Therefore a more direct linkage can be established step by step, from debt availability, through investment, to NOI growth.

[53]The impulse-response functions will tell a similar story in this regard.

[54]This is because, in a Gordon Growth Model, the yield should be defined as $r - g$, with g being NOI growth. If both the yield and NOI growth are persistent (which they are), they will predict each other.

4.2 Impulse Response Functions

We now examine the impulse-response functions from the full-sample VAR. These are presented in figures 3-11. In each figure we plot the value of the impulse-response, as well as 90% confidence bands, constructed using a bootstrap with 5000 iterations. We track impulse responses to 24 quarters.[55]

We begin by examining the impulse response of LTV to a shock in yield (Figure 3). This should be interpreted as a shock stemming from the discount factor and affecting asset values, since NOI growth is held constant. Note that LTV is also held constant, which may at first seem unintuitive, since asset values change. However, the asset values used in LTV are appraisals, which are known to lag transaction values, and can therefore remain constant initially, even when yields change. The plot shows an initially positive marginal response that increases for about four quarters, before decreasing and reverting back to zero after about seven quarters. Subsequently, the response turns negative, decreases to trough around 13 quarters, and then reverts 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 BG model would predict as the downward debt cycle is set in motion. An exogenous positive shock to yields (which we are simulating here) immediately makes LTVs rise, mechanically at first (since debt balances are constant but asset values have declined); this happens as appraisals catch up to transaction values. Subsequently as the market downturn continues, lending standards are tightened, and LTVs are then lowered, which makes debt even more scarce. The three-year time horizon for tightened lending standards actually to manifest in industry-wide LTVs seems plausible. This is because existing loans are only very rarely accelerated. Instead, new loans (if any) are made at lower LTVs while old loans still exist, and so the delevering of the entire market happens more gradually. The timing of lending standards' tightening also corresponds to the time when *pvs* becomes the dominant driver of LTV (see Figure 2). This indicates that the tightening of lending standards is contemporaneous with a general shift in risk appetite as the cycle deepens. The IRF of *pvs* on LTV in Figure 11 supports this idea. As predicted by the BG model, a significant delevering takes place.

We next turn to the impulse responses to shocks to LTV. Figure 4 shows the response of yield to such a shock. In principle, this is an orthogonal shock to LTV, without a change in yield. As such this could simply be interpreted as an increase in yield, required by equity's becoming more risky (increased likelihood of costly bankruptcy), because leverage has increased.[56] However, the timing shown in Figure 2, in which LTV becomes a relevant driver of yield only after 3 quarters,

[55]Note that we use unfiltered data, and work in a setting that constitutes a subset of the economy. For this reason, our impulse-response functions tend to show wider confidence bands than is often the case in the macroeconomics literature.

[56]The vast majority of players in this universe are tax exempt, and so the value created by the tax shield of debt is non-existent.

suggests a more complex interpretation. In the context of the BG model, a positive shock to LTV happens endogenously, at the beginning of the cycle, when asset values experience a shock (i.e. yields increase). Seen in this context, the impulse response in Figure 4 is the feedback of the BG debt cycle back into asset markets. The marginal response of yield begins at zero, but turns 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. The shock to asset values causes a rise in LTVs, which causes a debt scarcity. There are therefore two combining effects at play here, which cause asset prices to decline: firstly, the increased risk of equity, but secondly, later, the exacerbated debt scarcity, which makes levered investments infeasible.

The longer-term mechanism by which the downward debt cycle causes a decline in asset prices and output is through reduced investment. To document this transmission mechanism, we therefore next consider the impulse response function of LTV on investment. This is shown in Figure 5. The left panel shows the marginal effect of the shock to LTV. This is immediately negative, then reverts to a zero- and then slightly positive- effect (although the confidence bands do not go into positive territory). 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. The right panel of Figure 5 shows this. In the cumulative response, investment is significantly lower for at least eight quarters, and then slowly reverts back to its original level, although the point estimate does not reach this. These results are consistent with the predictions of the BG model: the onset of the debt cycle causes a decrease in investment, reflecting reduced debt availability. Investment eventually recovers after the cycle reaches its bottom. Note that investment can take the form of either building purchases or renovations. It is likely that, in the bottom of the cycle, building purchases will take place first, as property values have fallen enough to make low-leverage or even all-equity deals attractive. The uncertain nature of the marginal effects for investment, in conjunction with significant cumulative effects that support the debt cycle, suggests that this variable takes some time to adjust (stickiness). This is in line with the slow pace of realized investment in our setting, which we have argued throughout.

Having established the link to investment, we now examine how the reduced investment impacts other variables further along the chain. We first examine the response of yield to an investment shock; this IRF is shown in Figure 6. By default, the function shows a positive shock to investment. This leads to a reduction in yields, meaning an increase in asset values, which is both intuitive and unsurprising. However, this does constitute an important channel in the debt cycle, as this is ultimately responsible for the change in asset values in the longer term. In the downward portion of the BG cycle, we would see a reduction in investment, which leads to increased yields, meaning decreased asset values. This exacerbates collateral constraints and deepens the cycle.

Figure 7 shows the impact on LTV of an investment shock. Here, too, by default, the function shows a positive shock, leading to a short-term increase in LTV, reversion to zero, and a later significant increase. In the onset of the debt cycle, the shock to investment is negative: the resulting impulse response would show an initial decrease in LTV, followed by a reversion to zero and a subsequent strong and permanent decrease. The permanent decrease reflects the tightening of lending standards that occurs as the BG cycle deepens (and corresponds in timing to the period in which *pvs* becomes an important driver of LTV, per the FEVD for LTV in Figure 2). The initial downtick (that we would see in the inverted version of the IRF), is likely due to entrepreneurs' attempting to repay debt early on, when they stop investing. As we noted briefly in Section 3.2, in many cases, properties will have either a credit line secured on them which can be repaid, or more often a layer of mezzanine financing which takes the form of essentially preferred equity which can be repaid in part or in full. These debt tranches are usually much more expensive than the first mortgages secured on properties and therefore entrepreneurs will have the incentives to pay these back as quickly as possible if this capital cannot be deployed. These tranches are generally fairly thin, and so, as shown in the IRF, this effect will be small.[57]

The last response to a shock to investment we discuss is that of NOI growth (*ld.noi*), the output variable. These IRFs are shown in Figure 8. Given the ambiguous nature of the marginal response, we also show the cumulative IRF here. As is visible on the cumulative IRF (again, from a positive shock to investment), NOI growth increases, and then reverts back to zero. While again, this is an entirely plausible and unsurprising result, this is the final piece in the chain of effects that comes from the BG framework. Once again, in a debt-cycle downturn, there would be a negative shock to investment, and a decline in NOI growth (i.e. a reduction in output).

We have thus documented the entire BG mechanism operating in commercial real estate markets. A shock to asset values affects debt availability. The reduced debt availability affects asset prices directly, and also reduces investment. The reduced investment feeds back to cause further reduced asset values and further reduced debt availability, but also negatively affects output.

We now compare the effects of the collateral constraints we have just examined to those of ability-to-pay constraints. Figure 9 shows the effect of an *NmDebt* shock on yield (left side) and investment (right side). These are the ability-to-pay counterparts of what Figures 4 and 5, respectively, illustrate with respect to balance-sheet constraints. The response of yield to a positive shock in *NmDebt* is initially slightly positive, and then reverts to zero. This is the opposite direction of what we would expect if ability-to-pay constraints acted similarly to balance-sheet constraints in the BG mechanism. Our conjecture is that all that this IRF shows is a small mechanical relationship between the two variables, since both depend positively on NOI. The response of investment to an *NmDebt* shock is not significantly different from zero. Thus, while in this setting we find strong evidence for binding debt constraints based on entrepreneurial net worth, and their predicted effects in a cycle, we do not find evidence for binding debt constraints and equivalent effects for ability-to-pay constraints.

We also explore the relationship between *NmDebt* and LTV, to assess empirically whether

[57]In addition, in a downturn, the amount of cash available to retire such debt will also tend to be small.

balance-sheet constraints and ability-to-pay constraints are either complements or supplements. Figure 10 shows impulse-responses in both directions between LTV and $NmDebt$. Except for a very brief negative response of $NmDebt$ to a shock in LTV, these IRFs are not significantly different from zero. Thus, except for a possible substitution of the two types of credit constraints in the very short term, these two variables show no relationship with each other.[58]

Finally, we examine the impact of risk appetite (pvs) on LTV. This IRF (both marginal and cumulative) is shown in Figure 11. The response to a positive shock in risk appetite is a raised LTV.[59] This is an intuitive result: with increased risk appetite bankers are willing to lend more on the same collateral. However, in addition to this, the figure documents an important linkage, which we have observed before. Recall that in the FEVD for LTV (Figure 2), pvs becomes the dominant driver from about 7 quarters on. This is the time when the LTV response to a shock in pvs becomes positive in Figure 11, and it is approximately the same time at which the LTV response to the initial shock in yield (Figure 4) becomes negative. In a BG downturn, of course, we have a negative shock in risk appetite (which then lowers LTVs). This timing matches the tightening of lending standards in the downturn, and supports the argument raised before, that this tightening is part of an economy-wide decrease in risk appetite in the downward cycle. [60]

4.3 Flight to Quality

We turn now to the *flight to quality* feature of the BG model. We can test this feature in CRE: 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*.[61] 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 A and B 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, the lagged left-hand side variable, and quarterly changes in LTV in *Non-Core* MSAs the previous quarter ($\Delta Non.Core.LTV_{t-1}$). The lagged left-hand side variable is added so our main independent variable does not inadvertently show effects that come from persistence of the left-hand side variable. To only consider periods of delevering, we only use observations for which the two-quarter moving average in $\Delta Non.Core.LTV$ is

[58] Recall that the FEVDs also did not show the two credit variables to be drivers of each other.

[59] Recall that pvs is an economy-wide variable; therefore these relationships also document the interlinkage of the CRE world with the broader economy.

[60] In contrast, the IRF of pvs on $NmDebt$ (not shown to save space, but available upon request) shows no significant effect. This constitutes further evidence that ability-to-pay constraints are not widely used by lenders as a *debt spigot*.

[61] The economics of this distinction are discussed in Section 2.2.

negative. We use the moving average in order to filter out noise from observations in which there is a short-lived idiosyncratic decrease in leverage, to focus instead on more meaningful delevering events. If the *flight to quality* hypothesis holds, we should see delevering in *Non-Core* markets leading delevering in *Core*. 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 creates essentially a threshold regression.

Table 2 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 1.84). In Model 2, on the other hand, we find a positive and strongly significant coefficient (t-statistic of 3.05) on the interacted variable $\Delta Non.Core.LTV_{t-1} \times Quint1$. The $\overline{R^2}$ for Model 2 is .21, compared to .05 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.[62]

4.4 Low-Leverage Entrepreneurs (ODCE Funds)

We now turn to low-leverage entrepreneurs, in the form of ODCE funds.

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.inv* using only properties held by ODCE funds. Specifically, in this case, *log.yield* is simply a weighted average of NOI divided by appraisal value. We do note the use of appraisals in this context, as transaction-based valuations are not available. The implications of this are discussed in Section 3.3. The other two variables are constructed as before, but using only data from ODCE-fund properties.

For *log.ltv* and *log.nmdebt*, we retain the previous specification, using industry-wide loan-to-value ratios, and differences between NOI and debt, respectively. 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

[62] 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.

operate, just like the low-leverage entrepreneurs in the BG model. The null hypothesis of no knock-on effect implies no effect of debt scarcity on ODCE fund behavior. If we find similar effects for ODCE funds as for the whole industry, this would imply knock-on effects. The risk-free rate and risk appetite retain the same specification as above.

As before, we begin with the forecast-error variance decomposition results, and then look at the impulse response functions from this VAR. Figure 12 and Appendix Table C.2, Panel A, show the variance decomposition for yield. As before, this variable is very persistent. Looking at drivers of innovations in yield, we find here, too, that the credit variables play a prominent role. *NmDebt* is the dominant driver of innovations through 4 quarters, and after this, LTV becomes dominant, through 11 quarters. LTV accounts for around 10% of variation for most forecast horizons, while *NmDebt* accounts for slightly under 5%. At long horizons, the risk-free rate becomes the dominant driver, accounting for about twice the variation of LTV. Across all forecast horizons, LTV accounts for a much higher fraction of variance than risk appetite (constant around 2% of variation) and NOI growth (around 5% of variation). These results reject a possible null hypothesis that low-leverage investors are unaffected by the debt cycle. In fact, the amount of variation in the yields of ODCE-fund properties explained by LTV is of similar magnitude as it is for the entire portfolio.

A remarkably low percentage of variation in yield is accounted for by investment (less than 1% throughout). This fits the business model for ODCE funds: they pursue mostly passive long-term strategies, consisting of stabilized properties held primarily for income purposes. They typically do not undertake major renovations, nor do they look for large exit-profits derived from value-added strategies. Since investment in this setting consists of trades and CapEx, it seems intuitive that for the valuation of the portfolios of ODCE funds, such activity does not play a large role. On the contrary, the asset values of ODCE funds are actually hit directly by debt scarcity (without going through investment as a channel), since this causes a market-wide decline in asset values, which includes the assets held by ODCE funds.

We next examine the forecast-error variance decomposition for investment.[63] This is shown in Figure 12 and Appendix Table C.2, Panel B. Since ODCE funds, by charter, do not engage in property-turnaround strategies, their CapEx will be minimal. Therefore, for these funds, this variable becomes an indicator of trading activity, i.e. a signed liquidity variable. Looking at sources of innovation in this variable, we find that, from about 8 quarters forward, the yield becomes the dominant driver of variation. This is in line with economic intuition, as asset values are important drivers of liquidity.[64] Yield accounts for around 10%-13% of variation. Throughout the set of prediction horizons, LTV accounts for 5%-8% of variation, and *NmDebt* accounts for 2%-4% of variation. This means the two credit variables together account for around 10%-12% of variation,

[63]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.

[64]There is also a general understanding (albeit with limited empirical evidence) that Tobin's Q should drive investment in general. This result would constitute some evidence in favor of such a mechanism.

a similar amount to asset values. Again, establishing the two credit variables as important drivers of trading activity implies knock-on effects to low-leverage investors.

The first impulse-response function we examine is that of LTV on yield.[65] This is shown in Figure 13. The impulse response here is persistently positive, albeit significant only over shorter forecast horizons. Comparing this figure with the same impulse response for the entire sample (Figure 4) 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 percentage points after only two quarters, compared to an initial maximum of under two percentage points after four quarters, for ODCE funds. The response for the whole sample then reverts to around three percentage points by around ten quarters, while that for ODCE funds remains in that range throughout.[66] 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 feel 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 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 BG 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 is yet unclear.[67] We will disentangle this shortly.

The final impulse-response we consider here is the response of investment to a shock in LTV (Figure 14). Once again, for ODCE funds, this is essentially a signed trading volume variable. The responses (both marginal and cumulative) are qualitatively extremely similar to those for the entire sample (Figure 5). This indicates that investment 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. Since the investment measure for ODCE funds is essentially the net sale of properties by these funds, the effect in this setting is that debt scarcity causes property trades by these players to slow down substantially.

Once the downturn sets in, do ODCE funds profit by acting as buyers of last resort, or do they face losses to their assets, similar to levered funds? The first way to disentangle these two hypotheses is through economic reasoning. In order for ODCE funds to act as buyers of last resort, these funds would need to be able to raise new capital 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

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

[66] Recall that this is a log-log IRF, so these numbers apply to an effect size in log terms.

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

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 2.2, 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.

As first-pass empirical evidence on this matter, we run a regression of changes in ODCE funds' real estate assets on the left-hand side,[68] 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.[69] If ODCE funds acted as buyers in high-LTV situations, we would find positive coefficients here. These results strongly support the hypothesis that low-leverage investors suffer knock-on effects from the debt cycle in this market.

We now present evidence for the mechanism of redemption queues in preventing ODCE funds from acting as buyers of last resort in a downward debt cycle. 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, to generate at least indirect 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 as of 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 Appendix Table C.2 provides the variance decomposition for the log of cash for the core open-ended funds. As with other state variables, cash holdings are highly persistent, at least at short forecast horizons (up to 8 quarters). At longer horizons, the yield is actually the primary driver of cash holdings (even exceeding own-variable persistence), explaining up to 31 percent of variation. This result is consistent with the hypothesis that ODCE funds manage cash 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

[68]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.

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

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 a downward debt cycle simply constitutes one possible reason for a market downturn. Thus, the result that LTV explains about 10-12 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. It also lends some support to the hypothesis that redemptions act as an important mechanism in driving this. Also of note is the importance of *pvs* at short forecast horizons. The fact that cash reserves vary with risk appetite is consistent with the overall role of cash reserves in managing impending redemption requests.

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.

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 as buyers of last resort. Instead, cash seems to be used to cover redemptions, or possibly recapitalize properties.[70]

The evidence in this subsection is that, as in the BG world, low-leverage entrepreneurs are also affected by a downward debt cycle, once the cycle deepens sufficiently. The value of the assets of low-leverage investors also declines. We find no evidence for the opposing hypothesis that these funds would be able to profit as buyers of last resort. This is likely because they face capital outflows in a downturn and are therefore also unable to invest. This is an important prediction of the BG model and we are able to empirically document this here. Further, to our knowledge, we are first in the literature to document systematically the asset pricing outcomes for ODCE funds within the market cycle, and explore empirically the possible role of redemption queues in driving their behavior.

5 Conclusion

Both leverage and investment are crucial to the CRE market, but in the literature thus far, the issues of debt availability and investment have largely been examined separately. We model these dimensions of the CRE market jointly with two aims. First, we desire a more accurate picture

[70]This, in a larger sense, then resembles the mechanism that is causing fire sales in the paradigm described by Coval and Stafford (2007).

of the mechanisms that drive asset market outcomes of debt cycles, and second, we seek a better understanding of the relative importance of leverage supply. To do so, we use the well-developed conceptual framework of the Bernanke-Gertler debt cycle, and focus on modeling both CRE yields and investment activity in this context.

Methodologically, we use the Campbell-Shiller VAR augmented with discount-factor variables consisting of state variables that capture credit effects and investment activity. We consider forecast-error variance decompositions as well as impulse-responses from this estimation. We find that credit effects constitute the primary driver of innovations in yields; this happens either directly, or by driving investments, which then drive yields. The cycle perpetuates as yields conversely drive LTVs. This shows the importance of this feedback cycle to the asset market. We are able to rule out alternative hypotheses that credit availability is driven by ability-to-pay constraints, simply responds to anticipated output, or is just driven by risk appetite in the economy. Impulse-responses are as predicted by the Bernanke-Gertler model. We further find evidence for *flight to quality*, as well as knock-on effects where even the assets of low-leverage entrepreneurs are negatively affected, as predicted in the BG paradigm.

Our study thus underlines the crucial importance of a well-functioning debt market to a capital market such as CRE, 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, and we confirm this finding, confirming investment as the primary mechanism for this linkage. Therefore our study implicitly also highlights the crucial importance of a well-functioning debt market to overall economic output.

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Table 1: Geographic Data on MSA Portfolios for Flight-to-Quality Test

This table presents 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. These are markets constitute the respective property portfolios used for the *flight-to-quality* test. All rankings are done by total NCREIF portfolio value in a given market and quarter, averaged across time.

Panel A: 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 B: Ten Largest Non-Top-50 CBSAs.

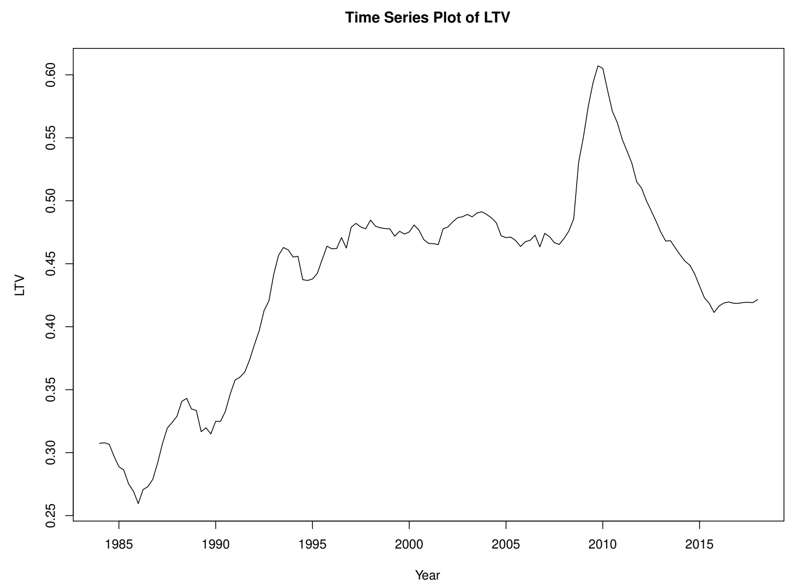
CBSA Name	**Average Portfolio Value (Million $)**
NH-Rockingham County-Strafford County	427
FL-Jacksonville	414
NJ-Camden	381
UT-Salt Lake City	375
NV-Reno	355
RI-MA-Providence-Warwick	327
HI-Urban Honolulu	323
PA-Pittsburgh	316
MI-Warren-Troy-Farmington Hills	305
TN-Knoxville	292

Table 2: 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: $\Delta Core.LTV_{t-1}$, the lagged dependent variable, $\Delta Non.Core.LTV_{t-1}$, 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)	0.001	0.0018
	(0.17)	(0.25)
$\Delta Core.LTV_{t-1}$	0.1404	0.1349
	(1.34)	(1.37)
$\Delta Non.Core.LTV_{t-1}$	0.2548	-0.0152
	$(1.84)^{\circ}$	(-0.09)
$Quint1$		-0.0094
		(-0.87)
$\Delta Non.Core.LTV_{t-1} \times Quint1$		0.8014
		$(3.05)^{**}$
	N: 72	N: 72
	$\overline{R^2}$: 0.0477	$\overline{R^2}$: 0.2123
	F: 2.78	F: 5.78

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



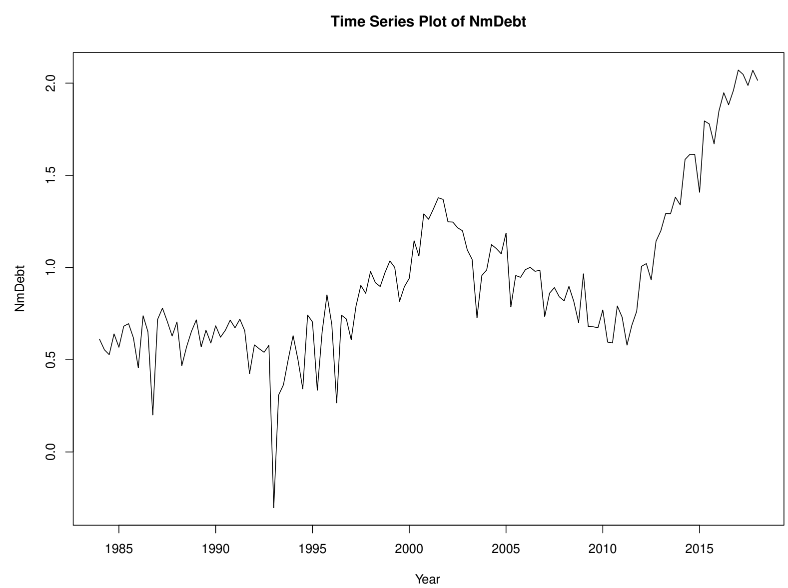
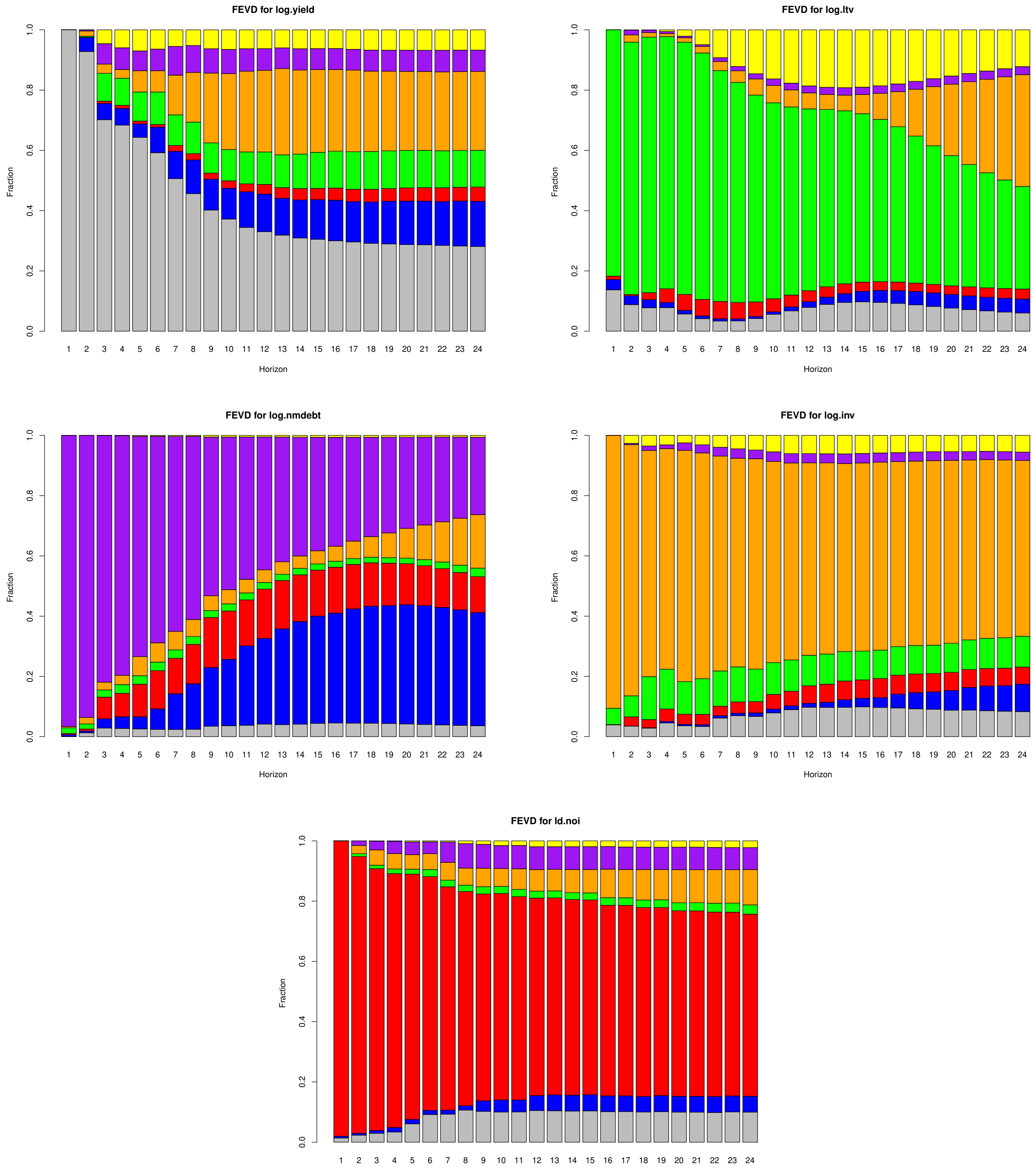


Figure 1: Time-Series Plots of LTV and NMDebt.

This figure shows time-series plots of the two measures of debt availability, loan-to value (LTV) and a modified debt service coverage ratio, calculated here as net operating income minus debt payments ($NmDebt$). The top panel in Figure 1 shows the variation in LTV for the properties in the NCREIF sample from 1982 through 2018. For the same sample period and set of properties, the bottom panel shows the value of $NmDebt$.



Colors: grey: *log.yield*, blue: *log.lt.rate*, red: *ld.noi*, green: *log.ltv*, orange: *log.inv*, purple: *log.nmdebt*, yellow:*log.pvs*.

Figure 2: Forecast-Error Variance Decompositions, full-sample VAR.

This figure shows the forecast-error variance decompositions for *log.yield*, *log.ltv*, *log.nmdebt*, *log.inv*, and *ld.noi*, 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), *log.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

Figure 3: Impulse-Response Function, *log.yield* on *log.ltv*.*

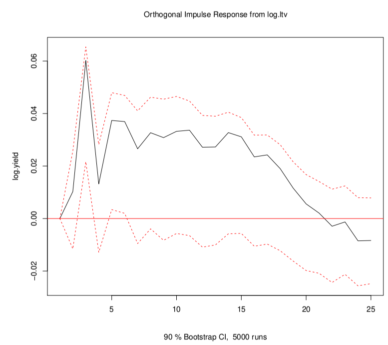


Figure 4: Impulse-Response Function, *log.ltv* on *log.yield*.*

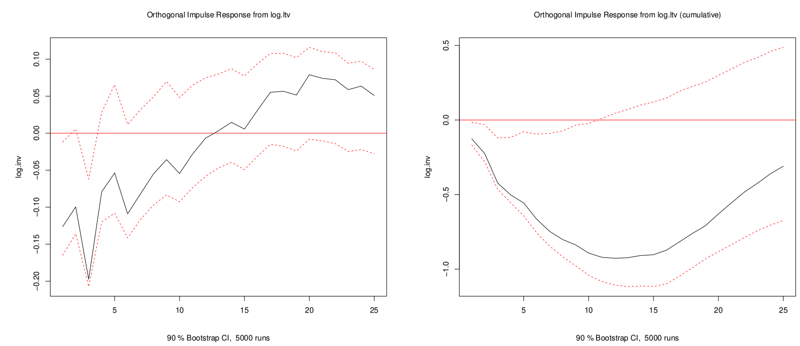


Figure 5: Impulse-Response Function, *log.ltv* on *log.inv*, marginal (left), and cumulative (right).*

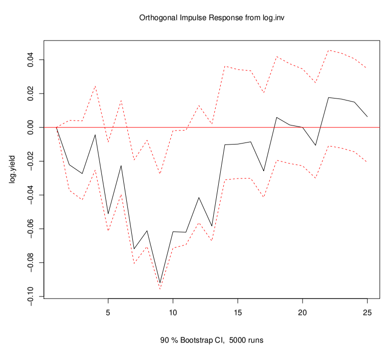


Figure 6: Impulse-Response Function, *log.inv* on *log.yield*.*

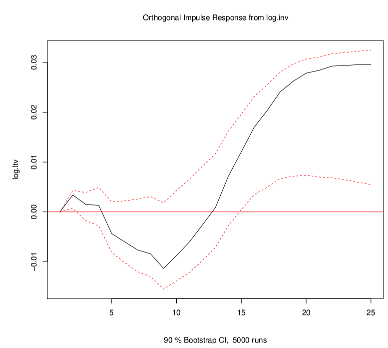


Figure 7: Impulse-Response Function, *log.inv* on *log.ltv*.*

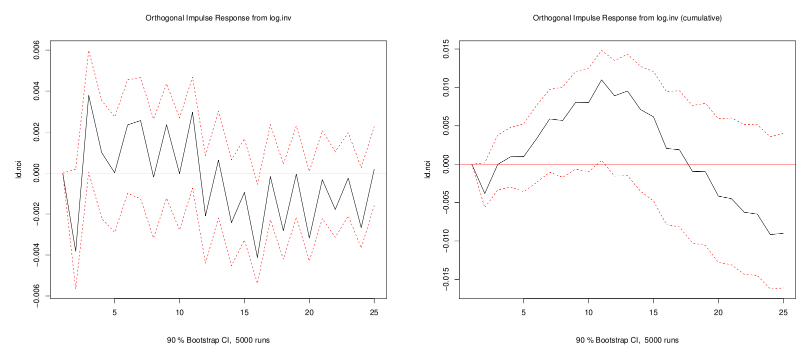


Figure 8: Impulse-Response Functions, *log.inv* on *ld.noi* marginal (left) and cumulative (right).*

*Figures 3–8: All figures show orthogonal impulse-response functions from the full-sample VAR. 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). 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.

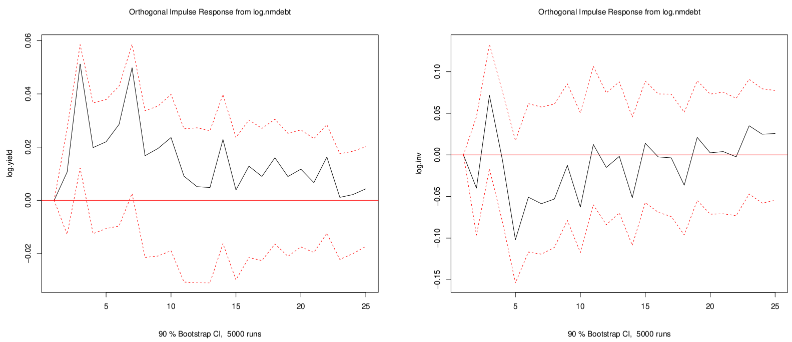


Figure 9: Impulse-Response Functions, *log.nmdebt* on *log.yield* (left) and *log.nmdebt* on *log.inv* (right).*

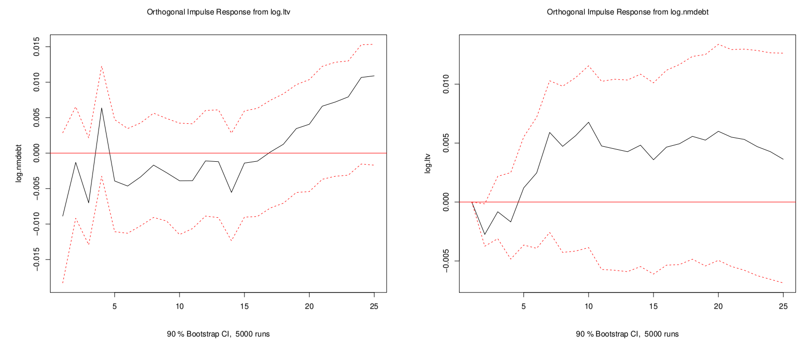


Figure 10: Impulse-Response Functions, *log.ltv* on *log.nmdebt* (left) and *log.nmdebt* on *log.ltv* (right).*

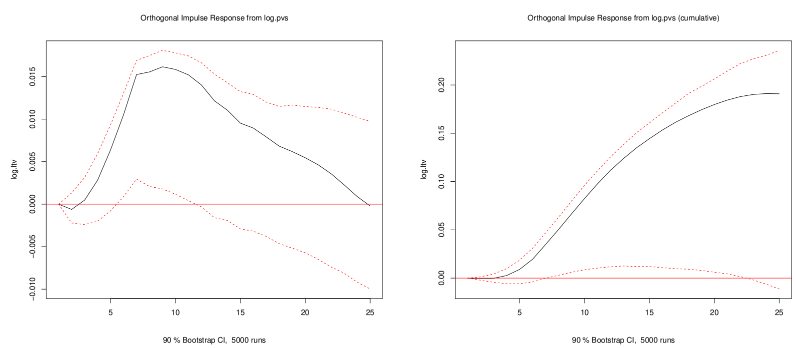
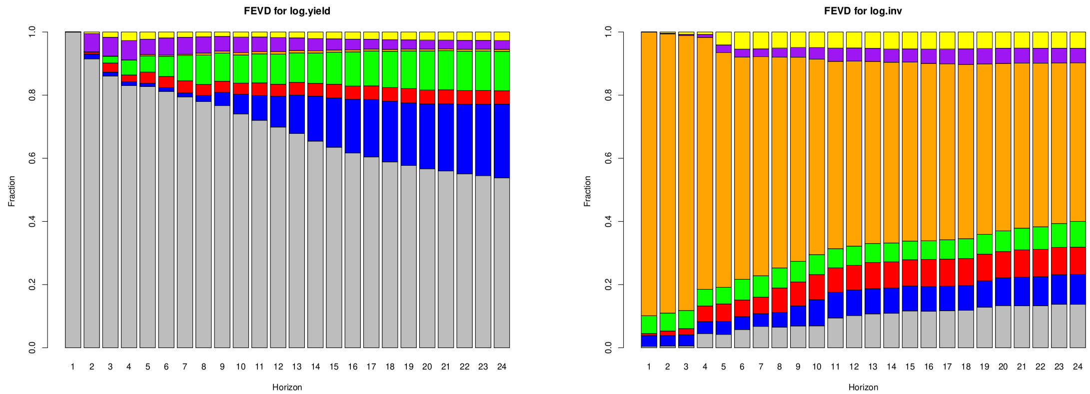


Figure 11: Impulse-Response Functions, *log.pvs* on *log.ltv* marginal (left) and cumulative (right).*

*Figures 9–11: All figures show orthogonal impulse-response functions from the full-sample VAR. 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). 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.



Colors: grey: *log.yield*, blue: *log.lt.rate*, red: *ld.noi*, green: *log.ltv*, orange: *log.inv*, purple: *log.nmdebt*, yellow: *log.pvs*.

Figure 12: Forecast-Error Variance Decompositions, Core Open-Ended Funds Only.*

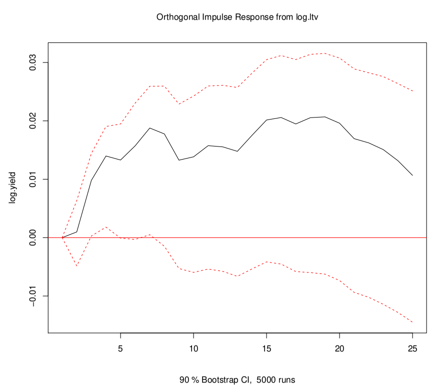


Figure 13: Impulse-Response Function, *log.ltv* on *log.yield*, Core Open-Ended Funds Only.*

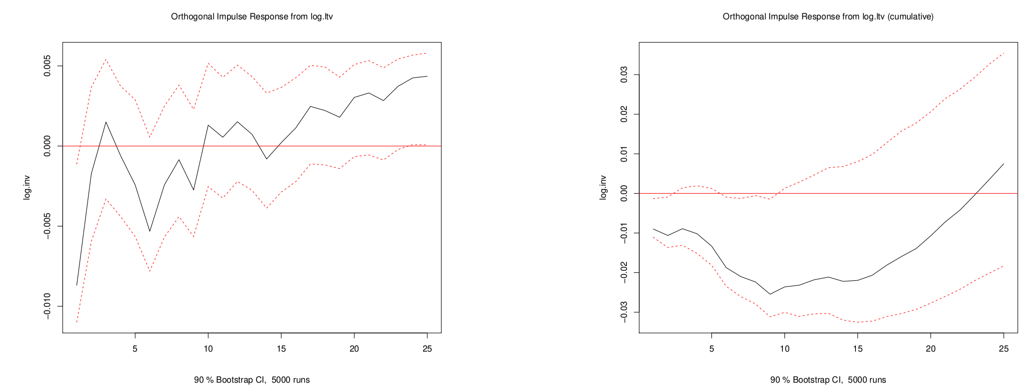
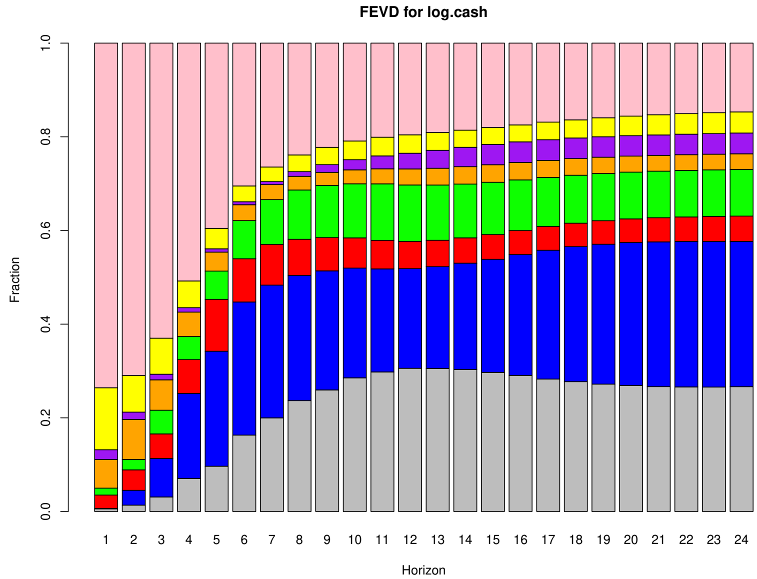


Figure 14: Impulse-Response Function, *log.ltv* on *log.inv*, marginal (left) and cumulative (right), Core Open-Ended Funds Only. *

*Figures 12–14: Figure 12 shows forecast-error variance decompositions for *log.yield* and *log.inv* from the VAR estimated with state variables aggregated over the properties held by Core Open-Ended Funds. Figures 13 and 14 show orthogonal impulse-response functions from the VAR estimated with 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). For this sample, *log.ltv* and *log.nmdebt* are the same state variables as for the full sample, while all other variables are constructed within the set of Core Open-Ended Funds. The risk-free rate and risk appetite remain the same across subsamples. All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags. For the IRFs, 90-percent confidence bands produced through a bootstrap with 5000 runs are shown by the red dashed lines.



Colors: grey: *log.yield*, blue: *log.lt.rate*, red: *ld.noi*, green: *log.ltv*, orange: *log.inv*, purple: *log.nmdebt*, yellow:*log.pvs*, pink:*log.cash*.

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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite), and *log.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 and risk appetite remain 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.

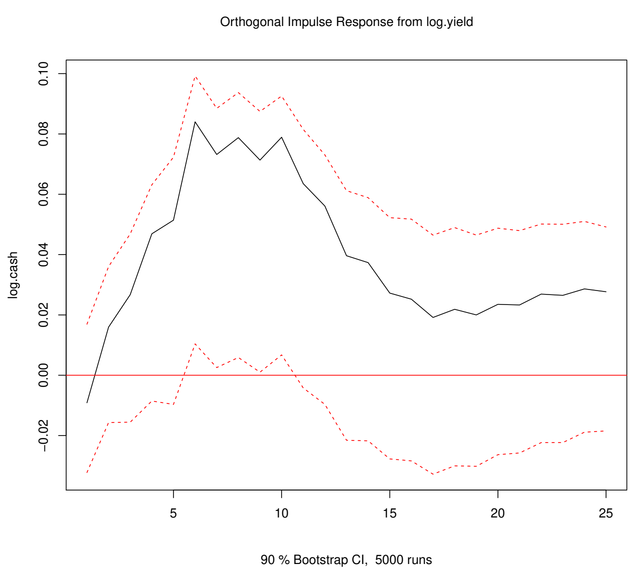


Figure 16: Impulse-Response Function, *log.yield* on *log.cash*, Core Open-Ended Funds Only.
This figure shows an orthogonal impulse-response function of *log.yield* on *log.cash*. The state variables for the VAR system are *log.yield* (the cash-flow yield), *log.lt.rate* (the long-term risk-free rate), *ld.noi* (the cash-flow growth rate), *log.ltv* (the loan-to-value ratio of a property), *log.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite), and *log.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 and risk appetite remain 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.

A Internet 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:

$$\begin{aligned} tot.ret_t &= \frac{P_t + C_t}{P_{t-1}} - 1 && (9) \\ app.ret_t &= \frac{P_t}{P_{t-1}} - 1 && (10) \end{aligned}$$

Here, P_τ is asset price at the end of period τ and C_τ is cash flow paid out over period τ.[71] Thus, the cash-flow yield $y_t = C_t/P_t$ for our weighted portfolio is constructed as

$$y_t = (tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} \qquad (11)$$

This is because

$$\begin{aligned} (tot.ret_t - app.ret_t) \times (app.ret_t + 1)^{-1} &= \left[\frac{P_t + C_t}{P_{t-1}} - 1 - \frac{P_t}{P_{t-1}} + 1\right] \times \frac{P_{t-1}}{P_t} && (12) \\ &= \frac{C_t}{P_{t-1}} \times \frac{P_{t-1}}{P_t} \\ &= C_t/P_t \end{aligned}$$

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.

[71] In reality, NCREIF conducts a more complex computation, for both appreciation return, and total return. For details on these, we refer the reader to NCREIF's website. In part, NCREIF subtracts capital improvements from the appreciation return that would be obtained by examining pure price change. This is so as to insure that appreciation returns show organic price growth, as opposed to price growth caused by capital injections by the investor. Since the derivation shown here simply relies on total return showing a true figure for income plus appreciation, and appreciation return showing a true figure for appreciation, we use this simplified representation without loss of generality.

B Internet Appendix: Main VAR Model with Baa Spread

In this section, we perform a robustness check by re-estimating the main VAR (Equation 3), using the natural logarithm of the spread of corporate Baa-rated bonds over 10-year Treasury securities (Baa Spread, or *log.baa*) instead of PVS, as the risk-premium variable. We obtain this data from the St. Louis Federal Reserve, and use quarterly averages. The data begins in 1986, so our analysis with this variable is slightly shorter than in the main specification.

This specification is subject to a tradeoff. On the one hand, there may be a concern that PVS captures risk appetite primarily in the public equity market. If capital markets are segmented, we may not fully capture risk-appetite dynamics in other markets, including the one we are examining (namely CRE). Baa Spread helps here, in that it captures risk preferences over a wider range of capital markets. This is why we estimate this specification of the VAR model.[72]

On the other hand, Baa Spread proxies for total risk premium (i.e. market price of risk times quantity of risk). By using the Campbell-Shiller framework we aim to decompose the discount rate (i.e. the risk premium), to determine the importance of credit constraints in driving this quantity. In this vein, including a proxy for the total risk premium as a driver of the discount rate is not as clean as including a measure of the market price of risk as a partial driver of the risk premium. In the specification which includes a proxy for the full risk premium, the model may suffer from over-identification, which in a forecasting setting is known to create noise. In spite of this, the above concern about risk preferences within- versus outside the market for common equity may be justified, and it is unlikely that one can find a reliable proxy for the market price of risk only, that is focused outside the stock market. The pure market price of risk is highly correlated with the total risk premium, and so this specification (subject to its limitations) should still lead to informative results.

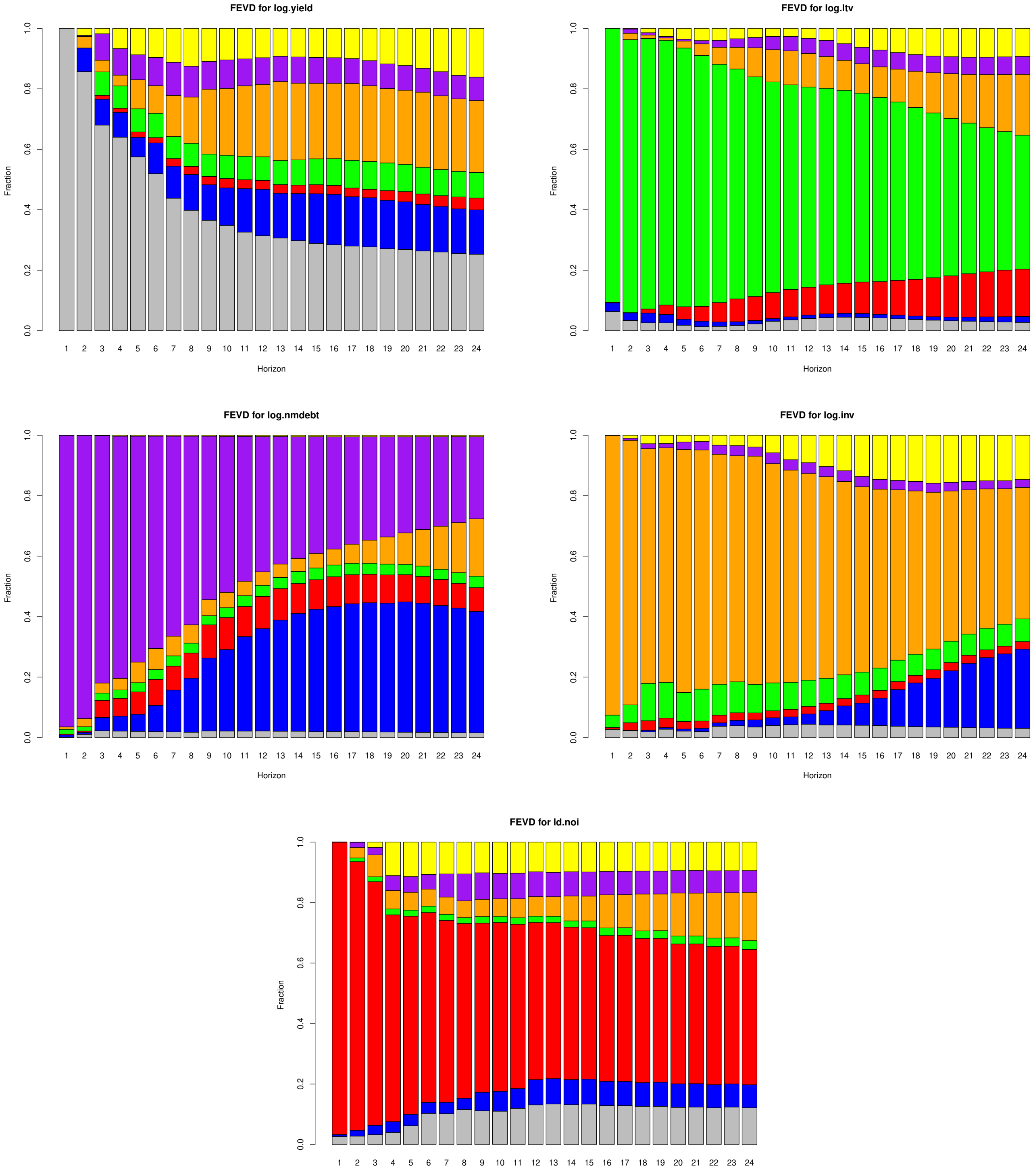
The results reported in Figures B.1–B.10 are from the VAR specification with the Baa Spread, and are analogous to those from the main VAR specification with PVS, reported in Figures 2–11. The figures show that the results are maintained very closely in this alternative specification. A few minor differences arise. In the FEVDs (Figure B.1), the two cash-flow derived measures, *ld.noi* and *log.nmdebt* take a more prominent role in driving LTV. This is consistent with economic intuition, in that the difference between PVS and the Baa spread is that the latter also contains a measure of the quantity of risk. Realized cash-flow volatility is a driver of asset-price volatility.

The IRFs, also show a very similar picture to that obtained in the main specification, with

[72] To proxy risk preferences in CRE even more closely, we also considered CMBS spreads. We were unable to find a long and reliable data series on these (in part because CMBS as instruments themselves do not date back far enough to allow reasonable VAR-based estimation at quarterly data frequencies). We did use BBB– Spread from Commercial Real Estate Direct, obtained via Bloomberg, to analyze correlation of CMBS spreads with Baa spreads. Over a 2012-2018 time period (where this data is reasonably available), we find a correlation coefficient of .67 between the two series, with a hypothesis test of zero correlation rejecting with a t-value of 5.186 and a p-value of $1.06e-5$. Thus, at least over the time sample in which we could measure this, there does not seem to be significant segmentation in the risk premium between corporate bonds and real estate debt.

PVS. One difference that arises is that, in the IRF for *log.yield* on *log.ltv* (Figure B.2), the shape of the point estimates is maintained (albeit the magnitude is slightly smaller), but the confidence bands are so as to make the medium-term downturn insignificant. This may largely be due to the noise introduced to the model by the overidentification discussed above.

The final IRF (that of *log.baa* on *log.ltv*, Figure B.10) yields a different interpretation from Figure 11 in the main model specification (which shows the IRF of *log.pvs* on *log.ltv*). First, a positive shock in *pvs* is bullish, as this is an increase in risk appetite, yielding, essentially a decrease in the market price of risk. A positive shock to the Baa spread is bearish, yielding an increase in risk premium. In any case, an increase in the required risk premium will cause a devaluation of assets, and therefore an increase in LTV. The sequence of events over time then becomes analogous to the primary BG asset price shock (represented in the IRF of yield on LTV). As the cycle deepens, lending standards are tightened, resulting in lower LTVs. Therefore this IRF looks very similar to the IRF for *log.yield* on *log.ltv* (Figure B.2), albeit with wider confidence bands, so as to make the effects largely insignificant (at least by a small margin). This is consistent with intuition: the Baa spread is an economy-wide measure of the risk premium, which does drive CRE yields; however, measuring CRE yields more directly in this context is obviously cleaner. The distinction between total risk premium, versus only the market price of risk brought about by using the Baa spread instead of *pvs* is therefore of great importance to the outcome for this particular IRF.



Colors: grey: *log.yield*, blue: *log.lt.rate*, red: *ld.noi*, green: *log.ltv*, orange: *log.inv*, purple: *log.nmdebt*, yellow:*log.baa*.

Figure B.1: Forecast-Error Variance Decompositions, full-sample VAR.

This figure shows the forecast-error variance decompositions for *log.yield*, *log.ltv*, *log.nmdebt*, *log.inv*, and *ld.noi*, 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), *log.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.baa* (risk appetite). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

Figure B.2: Impulse-Response Function, *log.yield* on *log.ltv*.*

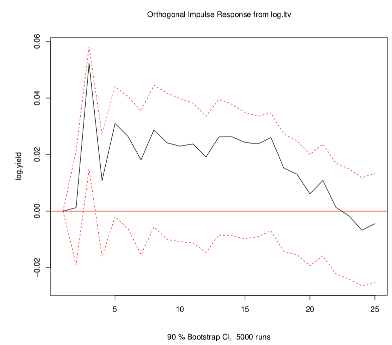


Figure B.3: Impulse-Response Function, *log.ltv* on *log.yield*.*

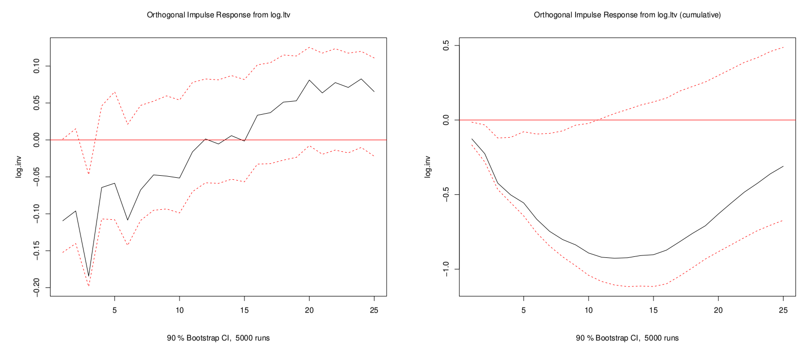


Figure B.4: Impulse-Response Function, *log.ltv* on *log.inv*, marginal (left), and cumulative (right).*

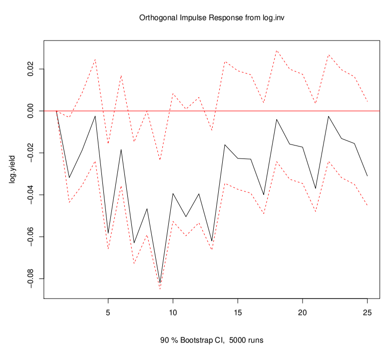


Figure B.5: Impulse-Response Function, *log.inv* on *log.yield*.*

Figure B.6: Impulse-Response Function, *log.inv* on *log.ltv*.*

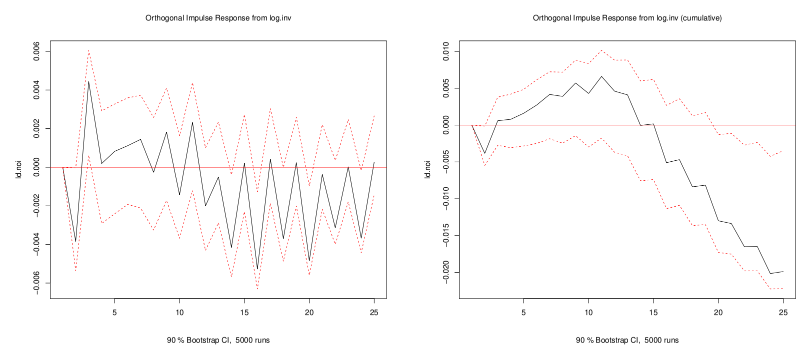


Figure B.7: Impulse-Response Functions, *log.inv* on *ld.noi* marginal (left) and cumulative (right).*

*Figures B.2–B.7: All figures show orthogonal impulse-response functions from the full-sample VAR. 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.baa* (risk appetite). 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.

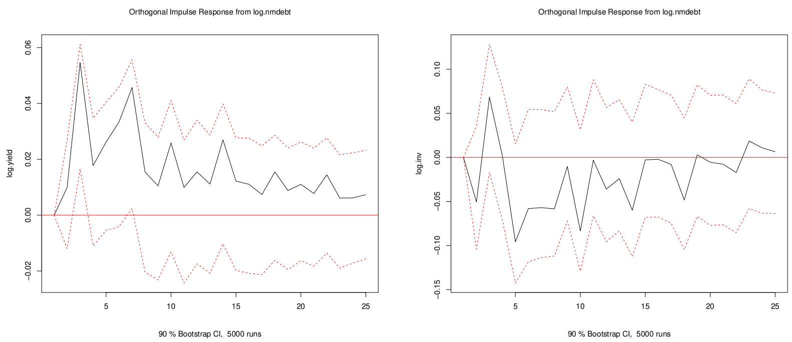


Figure B.8: Impulse-Response Functions, *log.nmdebt* on *log.yield* (left) and *log.nmdebt* on *log.inv* (right).*

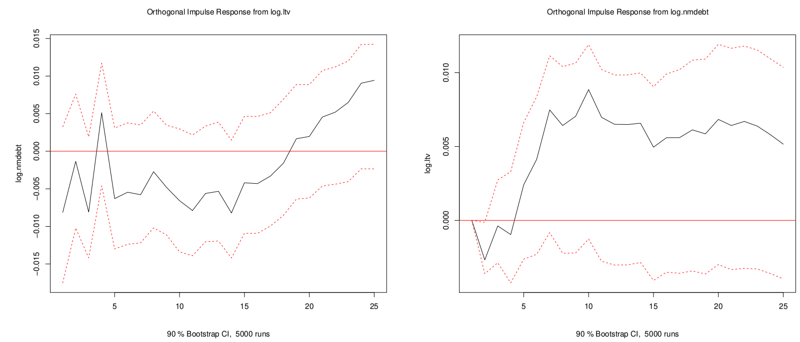


Figure B.9: Impulse-Response Functions, *log.ltv* on *log.nmdebt* (left) and *log.nmdebt* on *log.ltv* (right).*

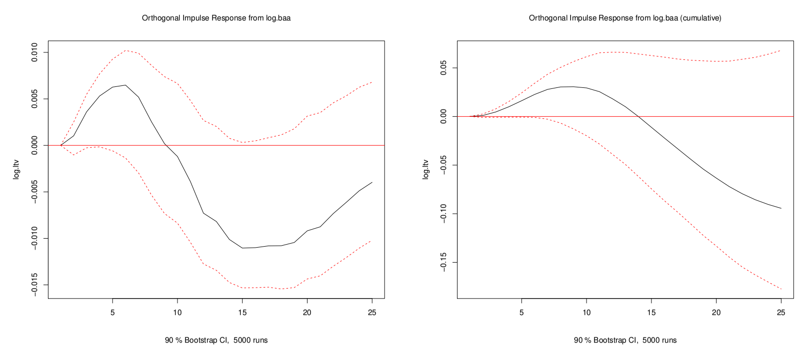


Figure B.10: Impulse-Response Functions, *log.baa* on *log.ltv* marginal (left) and cumulative (right).*

*Figures B.8–B.10: All figures show orthogonal impulse-response functions from the full-sample VAR. 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.baa* (risk appetite). 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.

C Internet Appendix: Tables for Forecast-Error Variance Decompositions

We show here the tables which detail the numerical values for the forecast-error variance decompositions conducted throughout the paper.

Table C.1: 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), *log.nmdebt* (Panel C), *log.inv* (Panel D), and *ld.noi* (Panel E), 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), *log.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). All variables are constructed as either natural logarithms or differences of logarithms. The VAR system uses 8 lags.

Panel A: *log.yield*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	1	0	0	0	0	0	0
2	0.928203	0.047004	0.000121	0.003665	0.016955	0.003931	0.000121
3	0.701903	0.054114	0.007404	0.092371	0.03055	0.067799	0.045858
4	0.683946	0.055292	0.010255	0.089968	0.028874	0.072163	0.059501
5	0.643337	0.044467	0.009479	0.096602	0.070355	0.065911	0.069848
6	0.592303	0.08501	0.008443	0.107911	0.070764	0.071773	0.063796
7	0.506477	0.090268	0.019244	0.101871	0.131749	0.095571	0.054821
8	0.45651	0.111958	0.020622	0.104801	0.1648	0.089369	0.05194
9	0.401916	0.102527	0.020313	0.100119	0.231694	0.080804	0.062627
10	0.37217	0.102275	0.024588	0.103602	0.252144	0.080323	0.064898
11	0.344406	0.118125	0.0265	0.105899	0.267619	0.074854	0.062597
12	0.330228	0.124864	0.031921	0.107731	0.270993	0.071838	0.062424
13	0.318787	0.122284	0.035374	0.108781	0.286362	0.068619	0.059792
14	0.309543	0.125978	0.037945	0.114237	0.278846	0.070822	0.062629
15	0.304724	0.131866	0.037267	0.119807	0.274511	0.069644	0.062182
16	0.30021	0.134665	0.040256	0.122265	0.270871	0.069864	0.061869
17	0.296305	0.133889	0.040896	0.124445	0.270822	0.069161	0.064482
18	0.291525	0.137251	0.042327	0.12514	0.266692	0.069969	0.067096
19	0.289733	0.141623	0.04195	0.125018	0.264316	0.069938	0.067422
20	0.287504	0.144279	0.043782	0.124272	0.262252	0.070409	0.067502
21	0.286893	0.14468	0.044842	0.123673	0.261745	0.070379	0.067788
22	0.28465	0.145532	0.045832	0.122705	0.261838	0.071728	0.067715
23	0.282861	0.149243	0.045532	0.121855	0.262028	0.071233	0.067249
24	0.281218	0.14987	0.047495	0.121581	0.261932	0.070803	0.067102

Panel B: *log.ltv*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	0.137336	0.034117	0.01141	0.817137	0	0	0
2	0.088174	0.029411	0.004347	0.837415	0.024069	0.015783	0.000802
3	0.07765	0.026784	0.023321	0.848203	0.014626	0.008762	0.000653
4	0.077978	0.017041	0.045649	0.83707	0.009803	0.007012	0.005446
5	0.056958	0.012219	0.052884	0.837053	0.01461	0.005293	0.020983
6	0.041567	0.009121	0.054629	0.817948	0.021725	0.00572	0.049289
7	0.033657	0.007617	0.057601	0.765907	0.030317	0.01257	0.092331
8	0.034004	0.006705	0.054852	0.73006	0.0383	0.014511	0.121566
9	0.042058	0.006921	0.048055	0.686497	0.053375	0.017465	0.14563
10	0.056168	0.008079	0.043318	0.650442	0.057471	0.021749	0.162772
11	0.067324	0.013117	0.039534	0.624098	0.056593	0.022555	0.176779
12	0.078989	0.018835	0.036418	0.603598	0.052939	0.023175	0.186046
13	0.089086	0.02401	0.03417	0.588775	0.049658	0.023718	0.190582
14	0.095254	0.029718	0.032179	0.574149	0.052047	0.024725	0.191928
15	0.097546	0.03486	0.030459	0.559	0.063426	0.024603	0.190107
16	0.095659	0.03971	0.02891	0.538649	0.086218	0.025085	0.185769
17	0.092311	0.042297	0.028359	0.515444	0.116582	0.025605	0.179402
18	0.087372	0.044312	0.027816	0.48808	0.155249	0.026343	0.170828
19	0.082072	0.044999	0.028227	0.460091	0.196039	0.0266	0.161973
20	0.076704	0.045043	0.028822	0.432117	0.236897	0.027314	0.153104
21	0.071843	0.045261	0.02994	0.406224	0.274476	0.027546	0.144709
22	0.067422	0.04549	0.030951	0.381877	0.310095	0.02758	0.136586
23	0.063562	0.045789	0.032351	0.360013	0.342041	0.027259	0.128985
24	0.060352	0.046231	0.033326	0.340341	0.371013	0.026765	0.121971

Panel C: *log.nmdebt*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	0.000563	0.006286	0.003757	0.01869	0.004434	0.966271	0
2	0.012983	0.0057	0.006796	0.016941	0.021362	0.936219	0
3	0.028772	0.030833	0.071758	0.023644	0.026012	0.81842	0.000562
4	0.027442	0.038699	0.077792	0.029001	0.030727	0.795457	0.000884
5	0.025788	0.040505	0.107876	0.028092	0.063512	0.731557	0.00267
6	0.024041	0.068292	0.126701	0.02851	0.063926	0.685813	0.002717
7	0.023864	0.118591	0.117755	0.027809	0.061337	0.647562	0.003082
8	0.024601	0.15113	0.130749	0.025936	0.056477	0.608196	0.002911
9	0.034618	0.194985	0.165885	0.023217	0.049119	0.526813	0.005363
10	0.036475	0.220378	0.160392	0.023477	0.047151	0.506786	0.005341
11	0.03787	0.263524	0.152521	0.023209	0.044975	0.472586	0.005315
12	0.041952	0.28402	0.163882	0.02177	0.042068	0.441263	0.005044
13	0.039896	0.318088	0.160411	0.02054	0.041446	0.414144	0.005475
14	0.041543	0.340668	0.154946	0.021733	0.04086	0.394477	0.005772
15	0.044203	0.355961	0.152542	0.020832	0.043432	0.376728	0.006301
16	0.045438	0.364609	0.152375	0.020032	0.049633	0.361582	0.006331
17	0.044964	0.379228	0.147657	0.019106	0.058062	0.344841	0.006142
18	0.044809	0.38846	0.143756	0.018354	0.068515	0.329954	0.006152
19	0.043757	0.391256	0.140846	0.018321	0.082038	0.317849	0.005933
20	0.042257	0.395908	0.135817	0.018377	0.098896	0.302988	0.005756
21	0.040777	0.39425	0.132375	0.02006	0.115294	0.291703	0.005542
22	0.03921	0.389808	0.128756	0.021982	0.13355	0.281305	0.005388
23	0.037521	0.383579	0.124012	0.024163	0.155879	0.269316	0.005531
24	0.036181	0.375722	0.119072	0.028463	0.177355	0.257074	0.006134

Panel D: *log.inv*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	0.039597	0.000226	0.000613	0.053896	0.905668	0	0
2	0.034769	0.000583	0.030475	0.069675	0.833786	0.004308	0.026405
3	0.02848	0.00135	0.02694	0.14259	0.750508	0.014768	0.035365
4	0.04537	0.005248	0.041334	0.131989	0.732051	0.012532	0.031477
5	0.036021	0.004879	0.033806	0.107959	0.767505	0.025024	0.024807
6	0.034128	0.005688	0.034317	0.11813	0.749383	0.027148	0.031205
7	0.061863	0.007597	0.031574	0.117135	0.712984	0.029332	0.039514
8	0.069772	0.008209	0.037366	0.116227	0.692343	0.031611	0.044471
9	0.06739	0.01174	0.037283	0.107686	0.698232	0.02908	0.04859
10	0.078943	0.012843	0.048586	0.105238	0.667986	0.031724	0.054679
11	0.089778	0.012562	0.048516	0.103758	0.653711	0.03119	0.060485
12	0.097621	0.013069	0.058162	0.101286	0.638715	0.030663	0.060484
13	0.097222	0.016976	0.060006	0.100124	0.634257	0.03031	0.061105
14	0.0975	0.025055	0.062236	0.097814	0.623866	0.032106	0.061423
15	0.099138	0.028588	0.060809	0.095597	0.624212	0.031552	0.060105
16	0.097161	0.032499	0.063901	0.093554	0.623949	0.030596	0.058339
17	0.095394	0.045947	0.062857	0.094536	0.613984	0.030028	0.057255
18	0.09237	0.053727	0.061944	0.094324	0.611979	0.030227	0.055428
19	0.090702	0.058	0.06085	0.093993	0.612544	0.029776	0.054135
20	0.087827	0.065292	0.060702	0.096121	0.607127	0.02883	0.054101
21	0.088094	0.07529	0.059405	0.098481	0.596792	0.028223	0.053714
22	0.086311	0.081806	0.058109	0.100267	0.59299	0.027566	0.052951
23	0.084664	0.085063	0.057694	0.101002	0.589566	0.02798	0.054031
24	0.083399	0.09076	0.056901	0.102067	0.583474	0.027893	0.055505

Panel E: *ld.noi*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	0.013823	0.005949	0.980227	0	0	0	0
2	0.023248	0.006154	0.918916	0.009356	0.027199	0.015127	0
3	0.029612	0.009087	0.86914	0.011297	0.051129	0.028612	0.001124
4	0.033819	0.014801	0.842576	0.015456	0.051061	0.040987	0.0013
5	0.060728	0.014992	0.813979	0.016433	0.048233	0.042069	0.003566
6	0.091933	0.013858	0.775722	0.023204	0.052711	0.039249	0.003322
7	0.092787	0.013833	0.740907	0.022028	0.058993	0.067747	0.003705
8	0.106708	0.014	0.711216	0.021112	0.056573	0.081228	0.009164
9	0.102239	0.03533	0.68622	0.024031	0.061327	0.079375	0.011477
10	0.100242	0.040166	0.684892	0.023651	0.059084	0.076539	0.015426
11	0.10055	0.039764	0.674516	0.023812	0.068776	0.077416	0.015166
12	0.104926	0.049724	0.655584	0.02301	0.071508	0.075748	0.019501
13	0.104378	0.052801	0.653821	0.022951	0.071445	0.075202	0.019402
14	0.103221	0.052957	0.6491	0.02282	0.076817	0.075806	0.019278
15	0.103896	0.053605	0.646467	0.023485	0.077487	0.07587	0.019189
16	0.101433	0.052285	0.632603	0.025257	0.094439	0.075273	0.018711
17	0.101803	0.051963	0.632248	0.025085	0.093825	0.074803	0.020274
18	0.100379	0.051231	0.627063	0.025034	0.101101	0.074461	0.020731
19	0.101452	0.053181	0.624098	0.025575	0.10055	0.07412	0.021023
20	0.099935	0.052476	0.615477	0.026732	0.109803	0.074709	0.020869
21	0.099734	0.052613	0.615322	0.027049	0.109532	0.074888	0.020861
22	0.098497	0.052953	0.612292	0.029213	0.111333	0.073916	0.021797
23	0.100596	0.053005	0.609765	0.03003	0.110822	0.073536	0.022246
24	0.099858	0.052567	0.604331	0.030931	0.117118	0.072838	0.022358

Table C.2: 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), *log.nmdebt* (Panel C), *log.inv* (Panel D), and *ld.noi* (Panel E), from the VAR estimated over state variables aggregated over properties owned by ODCE 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.inv* (investment), *log.nmdebt* (modified debt-service coverage ratio), and *log.pvs* (risk appetite). All variables are constructed as either natural logarithms or differences of logarithms. The 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*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	1	0	0	0	0	0	0
2	0.914937	0.014965	0.006347	0.000334	0.000785	0.057265	0.005368
3	0.860349	0.012387	0.028955	0.021275	0.000767	0.059387	0.016881
4	0.830532	0.012027	0.021282	0.046932	0.00087	0.0611	0.027257
5	0.827518	0.009779	0.035858	0.05125	0.004226	0.048477	0.022893
6	0.811845	0.011963	0.035165	0.063987	0.003857	0.054458	0.018724
7	0.79456	0.012753	0.038215	0.079789	0.003999	0.053754	0.016931
8	0.779776	0.019017	0.034979	0.09309	0.006396	0.051444	0.015299
9	0.766773	0.041766	0.035432	0.088922	0.006809	0.046127	0.014171
10	0.74066	0.061828	0.035567	0.088997	0.007668	0.049117	0.016162
11	0.720351	0.078335	0.04022	0.091746	0.007302	0.046276	0.01577
12	0.698687	0.097608	0.038192	0.0954	0.008147	0.044209	0.017757
13	0.678813	0.121278	0.040273	0.093391	0.007654	0.039935	0.018657
14	0.654235	0.14236	0.040602	0.096173	0.007282	0.038274	0.021074
15	0.634995	0.15625	0.043182	0.10154	0.006849	0.035517	0.021667
16	0.617091	0.169663	0.042066	0.108076	0.006689	0.033603	0.022812
17	0.604276	0.181833	0.043387	0.110155	0.006224	0.031174	0.02295
18	0.588587	0.191979	0.043396	0.114803	0.006116	0.030586	0.024534
19	0.577333	0.19828	0.045113	0.119138	0.005951	0.029419	0.024766
20	0.566891	0.205448	0.044072	0.123357	0.006074	0.028655	0.025504
21	0.560071	0.212639	0.044306	0.123683	0.006005	0.027641	0.025655
22	0.550983	0.219906	0.043509	0.124657	0.006212	0.028154	0.026579
23	0.545064	0.225943	0.043633	0.124647	0.006285	0.027826	0.026602
24	0.538203	0.233158	0.042583	0.124455	0.006578	0.027905	0.027118

Panel B: *log.inv*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*
1	0.00441	0.034449	0.006238	0.056381	0.898522	0	0
2	0.005637	0.033396	0.013952	0.056776	0.884294	0.002046	0.003899
3	0.005779	0.035138	0.01961	0.057473	0.870623	0.003809	0.007568
4	0.045042	0.037745	0.049478	0.052716	0.797812	0.009338	0.00787
5	0.042294	0.041332	0.055079	0.05259	0.743288	0.024506	0.040911
6	0.057713	0.040935	0.052488	0.065513	0.703822	0.025221	0.054309
7	0.067666	0.040362	0.052113	0.067714	0.693901	0.024836	0.053409
8	0.065395	0.046559	0.077338	0.063416	0.667585	0.028871	0.050836
9	0.068917	0.063443	0.07606	0.065158	0.646567	0.030652	0.049201
10	0.069158	0.083063	0.079615	0.063095	0.618972	0.036656	0.049441
11	0.094266	0.08136	0.077391	0.06061	0.593341	0.041973	0.051058
12	0.102065	0.080662	0.078169	0.0609	0.586157	0.041448	0.050598
13	0.107148	0.079759	0.083187	0.060024	0.576619	0.041462	0.051799
14	0.109399	0.079518	0.083046	0.059772	0.572323	0.041952	0.05399
15	0.116557	0.078878	0.083189	0.059226	0.566968	0.041683	0.053499
16	0.115898	0.078077	0.085713	0.059133	0.561569	0.04544	0.05417
17	0.117293	0.077458	0.085789	0.061286	0.557455	0.046857	0.053863
18	0.118531	0.078703	0.085318	0.062696	0.551713	0.049633	0.053405
19	0.128633	0.083763	0.083932	0.062698	0.539977	0.048627	0.052369
20	0.133575	0.087831	0.08332	0.06531	0.530306	0.048147	0.051512
21	0.133115	0.090185	0.086579	0.068786	0.522657	0.047543	0.051134
22	0.13281	0.092222	0.086499	0.071416	0.518235	0.047169	0.051649
23	0.138026	0.093427	0.086336	0.07558	0.508839	0.04636	0.051432
24	0.137535	0.094811	0.086067	0.081623	0.502457	0.045774	0.051734

Panel C: *log.cash*

Periods	*log.yield*	*log.lt.rate*	*ld.noi*	*log.ltv*	*log.inv*	*log.nmdebt*	*log.pvs*	*log.cash*
1	0.005786	0.000941	0.028383	0.014777	0.06115	0.020902	0.132302	0.735759
2	0.013567	0.031725	0.043671	0.022263	0.085472	0.015495	0.078115	0.709692
3	0.031058	0.082153	0.052516	0.050527	0.064912	0.011937	0.076902	0.629996
4	0.070597	0.181621	0.072201	0.049149	0.052127	0.009511	0.057035	0.507759
5	0.096666	0.245497	0.110816	0.060292	0.040469	0.007184	0.04361	0.395465
6	0.163089	0.284221	0.092382	0.081398	0.033887	0.006407	0.033697	0.304919
7	0.199989	0.283334	0.087044	0.095527	0.031993	0.006515	0.031052	0.264545
8	0.236707	0.267501	0.076972	0.10521	0.029215	0.010029	0.035609	0.238756
9	0.259568	0.254264	0.070984	0.111476	0.027824	0.016432	0.036976	0.222476
10	0.285456	0.234212	0.064568	0.115451	0.029755	0.021693	0.039891	0.208974
11	0.297986	0.22001	0.060908	0.120685	0.032088	0.027556	0.039842	0.200925
12	0.305791	0.21276	0.058202	0.120382	0.034261	0.033511	0.039343	0.19575
13	0.305355	0.217454	0.056249	0.117964	0.035793	0.038332	0.037942	0.190912
14	0.303136	0.22699	0.054172	0.11474	0.037189	0.041355	0.036524	0.185894
15	0.297022	0.241424	0.052851	0.111613	0.037468	0.043239	0.036139	0.180244
16	0.290608	0.258023	0.051212	0.108177	0.037131	0.044086	0.036165	0.174599
17	0.282757	0.275008	0.050742	0.104839	0.036276	0.044146	0.037554	0.168677
18	0.277248	0.288323	0.049931	0.102404	0.035586	0.04399	0.038723	0.163795
19	0.271952	0.298627	0.050335	0.100649	0.034818	0.043733	0.040533	0.159353
20	0.269004	0.305345	0.050433	0.099735	0.034261	0.043629	0.041719	0.155873
21	0.266588	0.309112	0.051593	0.099291	0.033771	0.043612	0.043123	0.15291
22	0.266057	0.310645	0.05221	0.099341	0.033531	0.043749	0.043912	0.150556
23	0.265698	0.3108	0.053418	0.099554	0.033339	0.043964	0.044701	0.148525
24	0.266536	0.310112	0.054033	0.09977	0.033286	0.044317	0.045119	0.146825