

Essays in Financial Economics

by

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To my parents, Barnali and Dilip K. Das, and my sister, Suchhanda

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ABSTRACT

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Chair: Stefan Nagel

My dissertation is a collection of three essays relating to three important aspects of financial markets - assets, firms, and households. While the first two chapters focus on financial linkage between asset markets (emerging country CDS and bonds), and firms (US financial system), the last chapter explores how households form beliefs about the stock markets and macroeconomy in general.

In the first chapter I show that the emerging market CDS-bond basis systematically declines when US interest rates fall. This is intriguing because in a frictionless market, the CDS-bond basis, defined as CDS spread minus bond spread should be zero. The basis deviations are temporary and occur in both pre and post the financial crisis of 2008-09, although the effect is arguably stronger post crisis. The relationship is driven by a rise in investor demand to sell CDS when US rates are low and the investor motive is most consistent with *reaching for yield*. Aggregate outstanding sovereign CDS positions held by investors show net CDS sold increases when the rates fall. I

also find the largest mutual funds in the emerging debt market are net sellers of CDS during 2006-2016 and show similar sensitivity to interest rates.

The second chapter is joint work with Sumanta Basu, George Michailidis, and Amiyatosh Purnanandam. We introduce and estimate a model that leverages a system-wide approach to identify systemically important financial institutions. Our Lasso penalized Vector Auto-regressive (LVAR) model explicitly allows for the possibility of connectivity amongst all institutions under consideration: this is in sharp contrast with extant measures of systemic risk that, either explicitly or implicitly, estimate such connections using pair-wise relationships between institutions. Using simulations we show that our approach can provide considerable improvement over extant measures. We estimate our model for large financial institutions in the U.S. and show its usefulness in detecting systemically stressful periods and institutions.

The third chapter is joint work with Camelia M. Kuhnen and Stefan Nagel. We show that individuals' macroeconomic expectations are influenced by their socioeconomic status (SES). Individuals with higher income or higher education levels are more optimistic about future macroeconomic developments, including business conditions, the national unemployment rate, and stock market returns. In the time series, the spread in beliefs between high-SES and low-SES individuals diminishes significantly during recessions. We document that SES-related differences in macroeconomic expectations are in part driven by different recent changes in people's personal finances, the type of news they attend to, and the economic conditions in their county of residence. Moreover, we find that SES-driven expectations can help explain why, during non-recession periods, individuals with higher socioeconomic status have more exposure to the stock market and are more inclined to purchase homes, durable goods, or cars.

CHAPTER I

Effect of US Monetary Policy on Emerging Sovereign CDS-Bond Market

1.1 Introduction

The CDS-bond basis is the difference between the cost of insurance on a risky bond and the bond's yield spread over a risk-free rate. In a frictionless market without arbitrage opportunities the basis should be exactly zero. But in practice it is at most only approximately zero due to technical contract differences, and sometimes it deviates quite far from zero. During the 2008-09 crisis, the basis became extremely negative (lowest at roughly -700 bps for high-yield and -200 bps for investment-grade US corporate bonds). The literature suggests the cause of the unusual deviations was the rapid decline in liquidity in the bond market during the crisis driven by a combination of unprecedented rise in risk aversion, deleveraging by investors, shortage of capital at dealers and rising funding costs. The gap in the CDS-bond basis persisted for a few months before going back to normal as market conditions improved and the participants regained the ability to contribute capital to the bond market (*Duffie (2010)*).

While large persistent deviations attracted much attention, there are also time-

varying discrepancies in the CDS-bond relationship that have not been looked at, possibly because of their temporary nature and smaller magnitude. These deviations are intriguing because they reveal a systematic pattern - I find that the basis systematically varies with US interest rate fluctuations. I explore if *reaching for yield* - investors' propensity to buy riskier assets in order to obtain higher returns - can explain this. The CDS-bond basis is particularly useful here because it can distinguish the demand shocks arising due to yield chasing investors from the shocks to the fundamental creditworthiness of the underlying entity. Under the assumption that fundamental factors related to the credit risk are priced in the same way in the bond or CDS, the discrepancies in the basis, which is the difference between the CDS and bond spreads, capture the effect of factors orthogonal to the credit risk component. This paper studies the effect of a particularly important global factor, namely the US monetary policy, on deviations of the sovereign emerging market (EM) basis.

The reason to focus on EM is that policy makers in EM have been concerned about US monetary policy in connection with excess global liquidity since 2008-09 crisis. Many argue that loose monetary policy, including unconventional ones like quantitative easing (QE), has had considerable spillover effects in EM economies through volatility in capital flow, exchange rate fluctuations, rapid credit growth or inflation etc.¹ But the impact of US monetary policy on foreign financial assets is relatively less studied, with the exception of few recent examples such as *Chen et al. (2012)*, *Fratzscher et al. (2016)*, *Gilchrist et al. (2014)* and *Bowman et al. (2015)*. While there is some overall agreement in these studies that expansionary policies depressed credit spreads in EM, there is little clarity on whether such effect is only seen post crisis, or what are the channels of transmission.² This paper provides insight into these issues by studying

¹See for example *Ahmed and Zlate (2014)*, *Mishra et al. (2014)*, *Rai and Suchanek (2014)*

²Both *Fratzscher et al. (2016)* and *Chen et al. (2012)* suggest post crisis QE raised equity prices and

the distortions in the basis which is better suited than just prices to identify the effect of investor demand from fundamental factors related to creditworthiness of the underlying. To the best of my knowledge, this paper is also the first to show spillover effects of US interest rates to deviations from a no-arbitrage relationship in a foreign financial market.

The main hypothesis in this paper is that low interest rates in the US create incentives for investors to reach for yield in EM debt market, which is riskier than traditional safe instruments like the treasuries. To gain exposure to the underlying credit risk of the sovereign, the investors, possibly those with short investment horizons or more volatile need of capital, prefer to sell CDS over buying the underlying bond because CDS contracts have liquidity advantages over bonds with the same return profile. This creates a selling pressure in CDS markets which, in presence of constrained dealers, depresses the CDS premia and thereby, the basis.

The two key ingredients in this hypothesis are - a) why do certain investors choose CDS over bonds, and b) how does a demand pressure lead the CDS premia to become temporarily delinked from the underlying bond spread?

First, CDS market performs a liquidity transformation by repackaging the bond's default risk into a more liquid security which transfers risk efficiently between holders (*Oehmke and Zawadowski (2015)*). CDS markets are considered more liquid because they have lower trading costs such as lower margin requirements (*Garleanu and Peder-*

depressed credit spreads in EM. They both study only the unconventional period whereas *Gilchrist et al. (2014)* and *Bowman et al. (2015)* compare the impact of conventional (pre-crisis) as well as unconventional (post-crisis) policy measures on the international bond market. But, their findings are contrasting - while *Gilchrist et al. (2014)* finds monetary easing leads to narrowing of EM sovereign bond yield spreads only during the conventional period, *Bowman et al. (2015)* suggests the effects are similar in both periods. *Fratzscher et al. (2016)* discusses global portfolio rebalancing driving the effects and *Gilchrist et al. (2014)* suggests reaching for yield as a likely mechanism. These two mechanisms are not exclusive. However, reaching for yield is a more specific demand channel that is associated with greater risk-taking and is more likely when interest rates are low.

sen (2011)) or ease of transaction due to greater standardization (*Oehmke and Zawadowski (2017)*).³ The lower cost attracts investors who have short-term trading horizon and are susceptible to liquidity shocks to trade in the CDS market. *Oehmke and Zawadowski (2015)* shows theoretically that relatively optimistic long-term buy-and-hold type investors buy the bond whereas optimistic short-term investors sell the CDS, and both types of pessimistic investors buy CDS. *Oehmke and Zawadowski (2017)* finds empirical evidence that speculative trading is more concentrated in CDS markets due of its liquidity advantage. Second, CDSs are over-the-counter, sophisticated derivatives with fewer and specialized participants like big banks, hedge funds and other institutional investors like mutual funds. A small specialized market decreases the ability of the dealer to hedge all uncovered positions on one hand, but also lends them bargaining power against other investors (*Duffie et al. (2005)*). Thus, excess demand to sell CDS by investors can lead these dealers to lower the quoted premium to make up for the cost of being unhedged.

There are two testable implications for the hypothesis. First, it predicts a positive relationship between the US interest rates and the EM CDS-bond basis. I find this to be true for both the level and slope of the US yield curve during 2004-2014. Second, it predicts a negative relationship between the net CDS sold and the US interest rates. This also holds up in the data, both for aggregate CDS positions and for the largest mutual funds that invest in emerging market debt. What can unifiedly explain these observed relationships? I suggest investor demand driven by reaching for yield motives presents the most coherent narrative.

In the first part of the empirical analysis, time series regressions at weekly frequency

³The CDS contracts based on ISDA guidelines have more standardized contractual terms than the bonds which are split into different issues with different coupon, maturity, embedded options etc. *Oehmke and Zawadowski (2017)* shows that more fragmented a firm's bond issues are, the more attractive its CDS market is for trading credit risk.

show that the basis increases by 48-76 bps on average when the level of US yield curve increases by 100 bps. The effect is significant only in the conventional (pre crisis) period - not surprising given that short rate was essentially stuck at zero in the unconventional (post crisis) period. For the US yield curve slope, a 100 bps increase is associated with about 35-45 bps increase in the EM CDS-bond basis during both pre and post period.⁴ The response in the basis is temporary - the effect reverts in less than 4 weeks. The adjusted R-squared of these regressions are high - varying between 0.72 to 0.28 depending on whether the specification includes lagged regressors or not. Also, the effect of the US term structure on basis is robust across time which is confirmed by estimating the same regression over \approx 2-year rolling windows from 2004-2014.⁵

Next, in an event-study approach, I show that the basis falls on days of Federal Open Markets Committee (FOMC) announcements of expansionary policy. This strongly suggests that the effect of interest rates on the basis is causal in nature. I follow *Hanson and Stein* (2015) and use changes in 2-year nominal treasury rate around FOMC announcements as a proxy for monetary policy news about expected medium path of interest rates. I find a 100 bps change in the US Treasury is associated with 143 bps change in basis, measured over the same 2-day window during the post crisis period. There are two possible concerns before we can interpret the estimated coefficient as causal effect of monetary policy. First, Could an omitted factor be partly driving the comovement between basis and the treasury rate changes on the FOMC days? If this reverse causality argument were true, the estimated effect should not be distinct for FOMC and non-FOMC days. This is rejected in the data - the response of basis to

⁴There is little theoretical guidance whether the short rate or long rate is relevant for reaching for yield. Without a priori assumptions, I have included both the short and long rates in my time series regression and find both of them to be significant implying that the whole term structure of interest is relevant for deviations in basis.

⁵The positive relationship is robust to alternative specifications such as fixed effects model or daily or semi-weekly frequency specifications.

100 bps US rate change is nearly twice for FOMC days than the non-FOMC days during the unconventional period and the effect is both economically and statistically significant. Second, does the change in treasury on announcement days reveal macroeconomic news or Fed's monetary policy stance? Since the effect on the FOMC days is significantly different from non-FOMC days when macro news is more prevalent, FOMC announcements arguably reveal news about policy beyond just the economic content. Lastly it is unrealistic to assume that the Fed contemporaneously responds to the basis changes - FOMC meetings call for days of preparation and, unless it is a crisis situation, ensuring credit market's smooth functioning is arguably not one of Fed's core mandates. An analysis focused on just the QE announcements shows similar patterns - an expansionary QE announcement on average lowers basis by ≈ 14 bps (statistically significant) by the day after the announcement.

A concern here is whether the positive relationship between the CDS-bond basis and US interest rates is driven by the illiquidity of the underlying bonds. Is it possible, in absence of any demand shocks to the CDS spreads, when the risk-free rate rises the illiquid bond yield does not adjust causing the yield spread to fall, thereby causing the basis to increase? To address this, I measure the effect of FOMC announcements over increasing horizon (1,2,...,5 days after announcement) assuming that longer horizon will allow the yields to adjust accordingly. The reactions of the CDS over these horizons in the unconventional period show a 100 bps decrease in the treasury rate is associated with almost one-to-one decrease in CDS premia even after 5 days. On the other hand, there is some adjustment in the yield right after announcement, but after 5 days, the change in the yield spreads negligible. Thus, the slow reaction of the bonds possibly leads to some degree of mismeasurement of the basis right after announcement, but it is not enough to explain the overall positive reaction of the basis to US interest rate

found in the data.⁶

The discussion until now establishes that the basis declines when US rates fall. Next, using a sample of weekly aggregate sovereign CDS positions from the Depository Trust & Clearing Corporation (DTCC) from 2008-2016, I show that the net CDS sold by investors increases when the slope of the US yield curve declines.⁷ During the entire sample period, with the exception of a few months in end 2008, the dealers are net buyers of sovereign CDS. This supports the view that the net sellers are yield seeking investors because selling CDS is most consistent with speculative risk-taking motive. Furthermore, literature on over-the-counter derivative market describes that dealers are not able to hedge their positions right away due to search cost in finding a counterparty (*Garleanu et al. (2009), Duffie et al. (2005)*) and a derivative order flow that increases risk exposure of the dealers, will lead to a larger price impact (*Shachar (2012)*). This means a temporary increase in CDS selling by yield-oriented investors (non-dealers) further increases the dealers' risk, prompting them to reduce the quoted price to deter potential sellers, thereby intensifying the impact on basis.

To give an example of who the investors and dealers might be in the EM CDS market, I gather from CRSP, the list of US mutual funds that invest in emerging market debt (EMD) during 2006-2016. I collect the CDS holdings data for the largest among these funds from their quarterly investment filings (N-Q and N-CSR forms) to

⁶Another concern is that the CDS somehow overreact to the changes in interest rates compared to the bonds. It is, however, hard to justify why the CDS overreacts positively to interest rate rise around announcements. Also, if there is an overreaction, what should be the appropriate horizon for the CDS markets to correct? Results show that the CDS response over 5-days around the announcement is still comparable in magnitude to its response over 2-days. So it is unclear if overreaction can explain the observed pattern. Faster reaction in CDS is also more plausible in light of recent evidence by *Adrian et al. (2017)* who show that dealers facing more regulations post crisis have reduced liquidity in the bond markets.

⁷Although the public data does not provide the positions for only the emerging countries, the major part of this aggregate CDS data is likely to be comprised of EM as the CDS market of advanced countries is small.

the Securities and Exchange Commission of US (SEC). The final sample has 17 funds, chosen such that they primarily invest in EMD during the sample period and have at least 50 million USD as net assets at the beginning of 2006.⁸ I find these funds are net sellers of CDS, similar to what *Jiang and Zhu* (2016) reports for the largest corporate bond funds. The dealers in these CDS contracts constitute of a handful of big banks such as, but not limited to, Citi Group, JP Morgan, Deutsche Bank, Credit Suisse, Goldman Sachs etc. There is much heterogeneity in CDS usage over time and across the funds; there are some large funds who do not use CDS at all while some are net sellers of CDS with the net notional CDS sold exceeding 50% of total net assets on occasions. Lastly, time series regression of changes in net CDS sold as a % of net assets by these funds on change in US yield curve slope gives a negative and significant coefficient. This is consistent with the idea that institutional investors such as mutual funds reach for yield in EM CDS market. However, one need to interpret the result cautiously because the mutual funds only give a partial picture of the entire class of CDS investors; but at least in this limited sample, the sign of the coefficient goes in the predicted direction.

The deviations in the basis in response to the changes in US interest rates discussed in this paper are most consistent with reaching for yield by investors. The reasons why I suggest yield seeking is the most likely channel are the following. a) The most likely motive behind CDS selling is speculative risk-taking. In the low interest rate regime, CDS is a suitable instrument to take on credit risk and jack up returns because it represents a tail risk that is evaluated over a horizon exceeding an average managers term (*Rajan* (2006)). b) In absence of theoretical models of reaching for yield the empirical literature has looked for a positive relationship between the spreads of risky

⁸The smallest fund at the beginning of this sample has 65 million USD worth of net assets. Most of these funds grow to many times their size over the next decade.

debt and US interest rate (e.g. *Kamin and Von Kleist* (1999), *Eichengreen and Mody* (1998), *Arora and Cerisola* (2001)) which is what I find for CDS spreads in the FOMC event study. c) The positive relationship between spreads and rates is not specific to just risky EM sovereign debt; it also holds for the high-yield US corporate basis and not the AAA-rated investment-grade basis.⁹ Using the basis data for US corporate debt constructed in *Bai and Collin-Dufresne* (2013), regressions of weekly changes in high-yield corporate basis on changes of US interest rates gives similar results as the EM basis. Lastly, the effect on basis is stronger in the post period (at least in the FOMC analysis) when the reaching for yield concern has received the most attention.

1.2 Related Literature

Relative importance of fundamental factors versus global factors in determining the EM credit spreads has been an important empirical question.¹⁰ However, in explaining determinants of credit spreads, it is unclear what the global variables pick up when included in regressions with other correlated country specific factors. For example, if spreads increase as global interest rates rise, it is difficult to parse out whether decline in creditworthiness of the borrower, or global phenomena unrelated to the creditworthiness causes the spreads to rise. In this respect, the high frequency deviations in the basis studied in this paper focuses on the effect of non-fundamental factors, which, incidentally, are also much fast moving compared to the main determinants of credit risk such as GDP growth or debt level.

Recent studies on comovement across EM CDS assert a significant role of global

⁹I thank the authors, Jenne Bai and Pierre Collin-Dufresne for kindly providing me with this weekly time series of high yield and investment grade corporate basis from 2005-2014.

¹⁰See for example *Eichengreen and Mody* (1998), *Arora and Cerisola* (2001), *McGuire and Schrijvers* (2003), *Csonto and Ivaschenko* (2013), *Longstaff et al.* (2011), *Fontana and Scheicher* (2016)).

investors whose demand shocks translate into liquidity shocks for commonly held assets;¹¹ *Longstaff et al.* (2011) finds high level of comovement in EM CDS; *Karolyi and McLaren* (2016) reports the sharp capital outflow from many EM markets in response to Fed’s surprise announcement of phasing out their asset purchase program. I complement the findings in *Longstaff et al.* (2011) by documenting that EM CDS comove more than the bonds and global risk premiums such as VIX are more correlated with the first principal component(PC) in the CDS market than the first PC in the bond markets. I interpret the different degree of comovement as a sign that marginal investors in bonds and CDS markets are constrained in different ways and consequently respond to global conditions differently. This makes the case for an investor-driven wedge in the CDS-bond pricing (i.e. push factor as opposed to pull factor) more persuasive. A shortcoming in this approach is, just by studying comovement, one can not distinguish whether the investors’ funding shocks or risk-taking motives drive the demand. The main analysis in the paper outlined in the introduction above, however, makes the distinction - the positive relationship between the basis and US rates is driven by how the investors’ search for yield responds to changes in the rates and *not* by how the investors’ ability to contribute capital responds to the same.

Theoretical treatment of reaching for yield is still nascent. It is unclear which

¹¹In markets with frictions, *Barberis et al.* (2005) and *Brunnermeier and Pedersen* (2009a) describe how demand of a common investor can give rise to comovement among fundamentally unrelated assets. *Barberis et al.* (2005) discusses various ways correlated demand can generate comovement. In style/category view, investors allocate assets to broad classes of securities eg bonds/stocks/corporate/government debt etc based on past performance or fundamental news and as investors move funds in and out of a category, assets, even those with fundamentally different cash flows, comove. In habitat view, investors prefer a to invest in a subset of assets that are easier to invest in e.g. have lower transaction costs, lower capital requirement etc. In information diffusion view, some assets react to news faster than others and this gives rise to a common factor across assets with similar rates of information assimilation. *Brunnermeier and Pedersen* (2009a) show in a theoretical setting how margin constraints and dealer funding constraints can translate into demand shocks that generate comovements among assets. All these different mechanisms are likely to be relevant to bond and CDS markets.

investors reach for yield and when, to what extent this relates to productive risk taking versus excessive risk, and what motives or frictions could lead to such behavior. To the best of my knowledge, the only theoretical models of reaching for yield are discussed in *Acharya and Naqvi* (2016) and *Hanson and Stein* (2015). The key frictions are different in the two papers; the former uses asymmetric information between the principal and manager to incentivise reaching for yield and the latter uses non-standard preference for investors to do so. However, post 2008-09, there has been a renewed interest in reaching for yield among policy makers both in US and abroad (*Haltom et al.* (2013)). The concern is whether prolonged low interest rates can encourage excessive exposure, coordinated risk-taking, complacency about the extent of risk undertaken, all of which have the potential to create a systemic impact when the tail-risk unwinds in unfavorable states of the world (*Yellen et al.* (2011)).

In absence of theoretical guidance, literature has therefore relied on empirical evidence of reaching for yield. But based on the circumstances or type of institution, the modes of reaching for yield could be both subtle and varied. *Becker and Ivashina* (2015) finds that insurance companies attempt to enhance portfolio returns by investing in the riskiest corporate bonds within a risk rating. *Di Maggio and Kacperczyk* (2017) finds that, in low interest rate environment, money market funds either exit the market or change their product offerings by investing in riskier asset classes. *Choi and Kronlund* (2016) finds when the level and slope of the yield curve are low, the mutual funds not only actively shift their assets to riskier bonds but also experience higher inflows from their investors. *Stein* (2013) warns of non-price ways in which reaching for yield may show up - investors ‘agree to fewer covenants, accept more implicit subordination, and so forth, and high yield issuance responds accordingly’. This paper contributes to the empirical literature on reaching for yield by documenting how the CDS selling increases

and consequently the basis falls when US interest rates are lowered.

When it comes to risky bond spreads, sovereign or corporate alike, the popular narrative has been reaching for yield predicts a positive relationship between US rates and credit spreads. But there is disagreement in empirical evidence on this; while *Fontana and Scheicher* (2016) reports a negative relationship, *Arora and Cerisola* (2001) and *Gilchrist et al.* (2014) find a positive relationship. For bond spreads at issuance *Kamin and Von Kleist* (1999) finds no impact and *Eichengreen and Mody* (1998) finds mixed evidence. In this respect, my findings support a positive relationship between US interest rates and EM spreads.

This paper is related to a recent branch of literature that discusses dislocations driven by demand and inability of arbitrageurs to close it. *Borio et al.* (2016) shows how growing demand for dollar hedge from investors combined with limits to arbitrage by dealers, owing to lower balance sheet capacity or stricter risk requirements, have driven the violations of covered interest parity in currency markets since 2007. *Klingler and Sundaresan* (2016) show demand for swaps by underfunded pension funds coupled with balance sheet constraints of swap dealers can drive the swap spreads negative. Possibly this is also why it is not surprising that I find the overall time series behavior of the EM basis is not unique. Not only that it closely resembles the US corporate basis reported in *Bai and Collin-Dufresne* (2013) - slightly positive during the early sample period but turns quite negative during the crisis and remains below zero thereafter - but also the cross-currency basis in the post crisis period reported in *Du et al.* (2016). My paper is similar to *Klingler and Sundaresan* (2016) in other ways as well; in that paper underfunded pension funds prefer interest rate swaps over buying Treasuries because the swap requires modest investment compared to Treasury, thus, freeing up scarce funds that can be invested in high return yielding stocks. Their mechanism is

similar in spirit to the choice of CDS over bonds when reaching for yield in this paper.

This paper also contributes to the growing empirical literature on CDS usage by institutional investors. Recent literature finds mutual funds are net sellers of corporate CDS and CDS usage is more prevalent among bond mutual funds which are invested in relatively illiquid bonds, have high portfolio turnover and/or volatility, or have under performed in the past. Findings in *Guettler and Adam* (2010) and *Jiang and Zhu* (2016) show corporate bond funds are net sellers of CDS from 2004-2011 and their most frequent strategy is to sell single-name CDS to gain credit risk exposure. Partly contradictorily, *Aragon et al.* (2016) report that net buy-protection of corporate bond mutual funds increases over the pre-crisis period (2004Q1-2007Q2) but falls steadily from 2007Q3 to 2009 amidst concern of counterparty risk. They speculate that mutual funds become sellers later partly because high risk premium in the post period is attractive (yield-chasing) and partly to fill the void left by original sellers (dealers) whose market making ability is impaired due to capital constraints in post period. The findings in this paper is similar - several largest EMD mutual funds are net sellers of sovereign CDS and their CDS selling behavior is consistent with reaching for yield.

1.3 Background on the CDS-bond basis

What is a CDS?

CDS is an insurance contract written on the notional amount of a bond (corporate or sovereign) for a fixed period. If a credit event occurs, such as default on the bond, missed coupon payment or restructuring etc, the insurer has to pay the insured the difference between the notional (face value) and the market value of the bond. In turn, the insurance buyer has to make fixed periodic payments (premiums as a percentage of

the notional amount) to the seller until the maturity of the contract or the credit event, whichever occurs first. The gross dollar denominated CDS market has grown since 2004 from about 8 Trillion USD to about 30 trillion USD in 2011 and have decreased since then to about 10 trillion USD in 2017. The current net size of the market is 1 trillion USD.¹² It is a largely an over-the-counter dealer based market where institutional investors such as hedge funds, banks, mutual funds etc can participate. The CDS contracts are created by International Swaps and Derivatives Association, Inc (ISDA) and have become more standardized over time.¹³

Theoretical relationship between bond spreads and CDS spreads

In a frictionless market (e.g. no dealer margin or transaction costs), a CDS contract can be priced by no-arbitrage. Following *Duffie* (1999), consider a par floating rate risky bond that pays coupons $R_t + S$ until maturity and a par floating rate risk-free bond that pays R_t at the same coupon frequency and has the same maturity. A portfolio that consists of shorting the risky bond and investing in the risk-free bond, pays a spread of S until maturity or default, whichever occurs first, and receives $100 - Y(\tau)$ at default, where τ is the time of default, 100 is the par value of the riskfree bond and $Y(\tau)$ is the price of the risky bond at default. The payoff of this portfolio is the same as that of a CDS written on the risky bond; the buyer pays a fixed premium (also called credit spread) S until the contract expires or the credit event, and receives the difference of the par value and market value of the risky bond at the event. Thus, theoretically the CDS spread is equal to the bond spread and, therefore, the basis, which is the difference between the two, is zero.¹⁴ At origination of the CDS contract,

¹²Source: ISDA <http://www.swapsinfo.org/charts/swaps/notional-outstanding>

¹³For a detailed discussion of the CDS markets see *Jarrow* (2011)

¹⁴Another way to construct the theoretical basis using fixed coupon bonds is discussed in *Jarrow*

there is no exchange of cash between the seller and buyer of the CDS. The annuity premium is determined such that the value of the CDS contract at origination is zero i.e the expected value of the premiums to be paid equals the expected payoff to be received in case of default. After origination, the CDS market value can differ from zero, based on changes in the riskiness of the underlying or changes in market rates. *Duffie* (1999) notes that determining the premium is a more critical pricing problem for the market makers, while valuation post origination is more critical for investors facing mark-to-market calls.

Basis deviations in practice

In practice, the no-arbitrage relationship is only approximate. Some technical reasons for the deviations discussed in the literature are a) non par fixed coupon bonds are used in reality instead of par floating rate bonds, b) maturity and timing of the coupon payment on the bond and CDS may not be coincident, c) Interest rate accrual for CDS coupons and bond coupons not accounted for in base model. But these technicalities are unlikely to cause severe discrepancies in the pricing of CDS and bond. In presence of frictions, however, the deviations in basis from its theoretical level could be both large and systematic. To trade on a negative (positive) basis, the arbitrageur needs to purchase the bond through a repo (short sell the bond through a reverse repo) and buy

(2016). Consider a fixed coupon risky bond with a face value of 1 that pays coupon c^B and has maturity τ . Consider a fixed coupon risk-free treasury bond with face value 1, coupon c^T and the same frequency of coupon payment and maturity as the risky bond. Shorting the risky bond and investing in the risk-free bond generates the following cash flow: pay $c^B - c^T$ every period until default or maturity, and receive $B(\chi, \tau) - D(\chi, \tau)$ at default period χ , where $B(\chi, \tau)$ and $D(\chi, \tau)$ are the price of the risky and risk-free bond at default. Note that this cash flow is same as that accrued to a CDS buyer who pays premium c until default or maturity, whichever is earlier, and receives $B(\chi, \tau) - D(\chi, \tau)$ at default. Thus, by no-arbitrage, the CDS premium, c is given by $c^B - c^T$. Thus, theoretically, the basis, defined as the difference between the CDS spread and the bond spread is zero i.e. $basis = c - (c^B - c^T) = 0$. However, in reality the CDS buyer receives $1 - D(\chi, \tau)$ at default so the relationship is approximate.

(sell) CDS contract on the notional amount of the bond. The bid-ask spread for risky illiquid bonds at the beginning and termination of the repo could be large. Moreover, the scarcity of the underlying bond can pose further short selling problems. Other examples of transaction costs faced by investors are margin requirements and mark-to-market calls. In addition to transaction costs, market makers inability to hedge their positions perfectly can also affect the fundamental basis. Counterparty risk of the seller is also not accounted for in the theoretical relationship; concern about CDS seller's ability to pay in case of default can move CDS spreads away from the bond spreads. Stricter capital requirements may also cause violation of the no-arbitrage relationship.

Studies have shown that higher market volatility and tighter funding during the financial crisis led to rapid deleveraging in the bond markets and consequently drove the basis significantly negative for an extended period. In fact, the basis has remained below zero since the crisis until today and this is attributed to reduced ability to arbitrage in presence of stricter balance sheet regulations on dealers. In this paper, I discuss systematic deviations in basis in response to US monetary policy in both pre and post crisis period.

1.4 Data Description

This section describes how the basis is constructed from data and discusses alternative methods of computing the basis does not alter the main result.

1.4.1 Bond and CDS data

Daily yield-to-maturity (ytm) for bonds and CDS spreads are obtained from Bloomberg for 23 emerging countries for the period 1-Jan-2004 to 14-Nov-2014.¹⁵ For each country the bonds are chosen based on the following filters : outstanding amount between 2004-2014, maturity type 'Bullet' (i.e senior straight bonds with no embedded options), coupon type 'Fixed', currency denomination 'USD', market type 'Global and Euro-Dollar', and sector/industry type 'Sovereign'. For each country I collect CDS spreads for all available maturities, namely, 1,2,3,4,5,7, and 10 years. The yield spread and CDS premia are denoted in annualized percentage.

The list of the countries and data availability for remaining maturity 3-5 years is summarized in Table 1.1. The last column in Table 1.1 lists the average S&P rating for these countries. Most ratings are in the speculative category (BBB). All empirical analysis in this paper exclude Venezuela and Ukraine as the average volatility of these two countries is ≈ 280 bps which is much higher than ≈ 54 bps for the rest of the sample. The exclusion only affects the level of the basis during the crisis but does not affect the main regression results.

Construction of the basis

To obtain a daily yield series for any country in my sample, at each date, I take the ytm of the bond whose remaining maturity is closest to 5 years and no less than 3 years. The methodology of stringing together on-the-run bonds is a common practice that is followed by Bloomberg to create benchmark yield series for particular maturity. Following the literature, I use overnight indexed swap rate (OIS) as the reference

¹⁵Both ytm and CDS spreads are mid quotes (average of bid and ask) of the last price of the day. The list of EMs are based on IMF/World bank list of emerging countries. Many countries are dropped from final list due to unavailability of CDS or enough US dollar denominated bond data.

risk-free rate. The OIS rate is the geometric average the overnight effective federal funds rate over the term of the contract and is largely considered default risk free because there is no exchange of principal at the beginning of the contract. Treasury yields are not an ideal proxy for risk-free reference rate as they can be artificially low due to ‘flight-to-quality’. I linearly interpolate the OIS curve to match the remaining maturity of the yield series at each date. Country specific yield spreads are computed as $ytm(3-5\text{years})$ minus $OIS(3-5\text{ years})$. Similarly, the maturity-matched CDS spread is obtained by linearly interpolating the CDS spreads. The basis is defined as the difference between maturity-matched CDS spread and yield spread. Figure 1.1 plots the average EM spreads and basis at a weekly frequency. The weekly data is constructed using end-of-day Friday quotes. In all subsequent empirical analysis I use the basis at 3 to 5 years remaining maturity.

Alternative ways to construct the basis

Many studies use the EMBIG yield spreads for emerging countries constructed by JP Morgan but these spreads are constructed using bonds with maturities varying from 2 to 30 years. Although EMBIG yield spread is a continuous time series, my average yield spread is a cleaner measure of basis at different maturities. However, my average EM yield spread closely resembles the JP Morgan EMBIG series during the sample period 2004-2014.¹⁶

Fontana (2011) interpolates ytm of bonds to have exact remaining maturity of 5 years and constructs the basis as difference between 5 year CDS and the interpolated bond spreads. The choice between this method and mine comes down to choice of interpolating the ytm or the CDS. Interpolating the yield assumes a linear yield curve

¹⁶ See Figure 1.17 in Supplementary Results for comparison of EMBIG and my yield spread.

and involves interpolating two bonds which are likely to have different principal and coupons. On the other hand interpolation across similar liquidity assets is arguably better. If one assumes that all the bonds around a certain maturity bucket have similar liquidity while the CDS at different maturities are substantially different in terms of their liquidity, then interpolating the CDS might be more prone to bias. Combining the relevant issues, it is hard to argue which method will be more appropriate for my analysis. For robustness, I use the basis constructed following *Fontana* (2011) methodology as well but this does not affect my main result.¹⁷

Another alternative choice for yield spreads is to use the z-spread, defined as the parallel shift over the zero-coupon treasury yield curve. But *Nashikkar et al.* (2011) and *Bai and Collin-Dufresne* (2013) argue that z-spreads become less comparable to the market CDS spreads since the bonds trade away from par. They follow par-equivalent CDS (PECDS) methodology, originally developed by JP Morgan, to extract default intensities from (non-par) prices of bonds and then calculating a fair CDS premium consistent with the bond implied default probabilities. The basis is then computed as the difference between actual CDS minus the bond-implied PECDS. To construct basis this way is heavily model dependent. It is also not obvious if this method is more appropriate in the current problem. In fact, my main result also holds up in the corporate basis data constructed by authors in Bai and Dufresne(2013) using this methodology. The results are presented in Section 1.8.

1.4.2 Global variables relevant for basis deviations

Literature has investigated the role of global variables in explaining the CDS-bond basis deviations, either in the context of corporate (*Fontana* (2011)) or sovereign (*Fontana*

¹⁷ See Figure 1.18 and Table 1.15 in Supplementary Results for comparison between basis created by these methods.

and Scheicher (2016)) debt. In this paper the focus is on US monetary policy. So the key variables of interest are the level and the slope of the US yield curve given by the following:

- **Short rate (level):** 3 month OIS
- **Term premia (slope):** 10 year Treasury - 3 month OIS

Controls used in the empirical section are other risk factors identified in this literature.

Risk premium: 3 month Libor-OIS spread indicates short term banking credit/liquidity risk. The Libor is an uncollateralised funding cost at which banks lend to each other. OIS is an overnight swap rate that allows borrowing at a fixed rate (federal funds rate in US) and is considered risk-free as there is no exchange of principal. Libor-OIS rate indicates the risk premium associated with counterparty risk in uncollateralised funding.

Volatility premium: CBOE Volatility Index VIX is the expected risk neutral variance of US S&P500 index and is believed to capture the aggregate uncertainty in the economy. Another alternative is to decompose VIX into a) forecast based on realized volatility and b) volatility risk premium. Using them as controls instead of VIX does not change the main result in the paper. Therefore, for parsimony I use VIX in the main body of the paper.

Liquidity risk premium: 3 month OIS-Treasury spread is considered a measure of short term liquidity premium because both OIS and treasury rates are risk free but treasuries are the safest collateral. In times of market stress, the ois-tbill spread indicates a liquidity premium related to *flight-to-safety*.

Dealer health: Average of 5 year CDS of largest US banks is indicative of the health of the dealers and is used to control for the tightness of the dealer's capital constraints that can affect their ability to provide liquidity or incur risk in the CDS-

bond markets.¹⁸

Country specific control: Country-specific controls are less meaningful for the basis since there is little to suggest if country fundamentals impact CDS and bond spreads differently. Moreover, the fundamental determinants of spreads such as debt-to-GDP or GDP growth are reported monthly or quarterly and, therefore, not helpful to explain basis variation at a daily/weekly frequency. However, studies have reported that the CDS markets are more correlated with equity than bonds. Therefore, I include the average EM stock return created by MSCI as an additional control.

Data on these global variables are obtained at daily frequency from the federal reserve website and Bloomberg. Figure 1.2 shows the weekly levels of the global variables and the basis averaged across the countries during the whole sample.

1.4.3 Subsample periods

In all subsequent empirical analysis, I divide the sample into two monetary regimes: a) pre 11/25/2008 - a conventional policy period (1/1/2004 to 11/24/2008), and b) post 11/25/2008 - an unconventional monetary policy period (11/25/2008-11/14/2014) following *Gilchrist et al.* (2014) who identify 11/25/2008 as the beginning of non-standard monetary policy in the US. The federal funds rate has been close to zero since the beginning of the unconventional period. The first quantitative easing related announcement was made on 11/25/2008. During the unconventional period, the Fed implemented the non-standard monetary policy by a) purchasing large scale mortgage backed securities (MBS) and treasuries with an aim to improve the functioning of financial markets and stimulate the economy by reducing the longer-term interest rate,

¹⁸ The banks included here are Amex, bofA, Citi, Goldman Sachs, JP Morgan, Morgan Stanley and Wells Fargo.

and by b) forward guidance to communicate the future path of federal funds rate. It is evident in Figure 1.2 that the two periods are distinctly different for many of these macroeconomic variables. For example, VIX index and bank health measured by the 5 year CDS of major banks/dealers have both increased in level and become more volatile in the post period. The short rate given by OIS3month started falling towards the end of 2008 and has remained close to zero since.

1.5 Comovement in EM debt market

This section examines the comovement in the EM bond and CDS markets separately to test if degree of comovement in the two markets is different. Varying degree of comovement in the CDS and bond markets support the argument that the temporary wedge in CDS-bond basis is driven by different marginal investors in the two markets. This section serves as a motivation for the main hypothesis - since CDS markets have lower transaction cost than bond markets, they attract different types of investors, which in turn drives a systematic wedge in the CDS-bond pricing. The aim of studying the comovements is not to distinguish whether the investors differ in their risk-taking behavior or the funding constraints they face, but to assert that investor-related factors as opposed to fundamental factors (i.e. push factors as opposed to pull factors) play the dominant role in the basis deviations.

Why comovement arises in EM debt market?

High level of comovement has been reported in many financial markets in the context of rising global liquidity post crisis (*Miranda-Agrippino and Rey (2015)*). Theoretical models such as *Brunnermeier and Pedersen (2009a)* describe how investor's

funding liquidity shocks can translate to asset market liquidity and give rise to commonality across securities. In a world with frictions, *Barberis et al.* (2005) describes different ways in which comovement can arise via correlated demand shock even when the assets are not fundamentally related. Investors may choose to allocate funds at an asset class level instead of picking individual ones. This sort of *style investing* has become increasingly common in EM CDS markets with the trading of CDX.EM indices. The average notional size of the sovereign CDS index is ~ 100 billion USD during 2008-2016. Alternatively, the *information diffusion* view suggests that some assets are easier to trade or held by investors with faster access to news. Thus, assets which assimilate information at the same rate comove more.

Comovement in CDS versus bond markets

I start by showing that EM bond yield spreads and CDS spreads comove a lot (Figure 1.3). Commonality is often empirically detected by using principal component analysis (PCA) in which the standardized variables are decomposed into orthogonal factors of decreasing explanatory power. The degree of comovement is given by the percentage variance explained by the first principal component (PC) of weekly changes in spreads (bonds or CDS) and it is a summary statistic that increases when the spreads move together more. Since many countries have missing data, I use the pairwise correlation matrix to estimate the PCs. The first PC is obtained as linear combination of the standardised variables (changes in yield or CDS spread) with positive weights and essentially represents a level factor of the spread changes.

Table 1.2 reports two metrics of average commonality among weekly changes in bond yield spread and CDS spread for two subsample periods - conventional (1/1/2004 to 11/24/2008) and post (11/25/2008 to 11/14/2014). The first metric is a simple av-

erage of absolute pairwise correlation among the sovereign CDS or yield spread changes and is found to be higher for CDS than bonds in both periods. The second metric is the explained percent variation of first PC and is also higher in CDS than in bonds in both periods.¹⁹ The first PC explains 76(63)% variation in CDS spreads whereas the first PC of bond spreads explain about 53(41)% variation in the conventional (unconventional) period. The magnitude is similar to what others have found in the literature; *Longstaff et al.* (2011) reports the first PC explains 64% variation of monthly CDS spreads during 2000-2010. Fontana and Scheicher (2016) reports CDS markets are more interconnected than bonds for European Union sovereign debt during 2007-2012 period. Another interesting pattern is that comovement declines from pre to post period. Increase interconnectedness before the crisis has been also reported in the case of the US stock markets in *Billio et al.* (2012a).

Time series dynamics of comovement

Figure 1.4 graphs the time series of the percentage variation explained by the first PC of spreads changes using ≈ 2 years rolling windows. Results for both 2-day changes and weekly changes in spreads are reported for robustness. The 2-day changes are constructed using every alternate days (i.e. non overlapping observations) and weekly changes are constructed from Friday to Friday. For each rolling window, only countries with more than 50% observations are used, thereby reducing the number of available countries to vary between 11 to 15 across the windows.

The time series pattern shows commonality across CDS spreads has been increasing over the last decade whereas it is declining for yield spreads. One has to careful before interpreting rising commonality as increased interdependence as it could also be driven

¹⁹ In calculating measures of comovement, countries with more than 50% missing observations are removed, leaving only 15 countries' to be included in Table 1.2

by increasing volatility of the underlying factor (*Forbes and Rigobon (2002)*). At least, the diverging pattern of comovement in the two markets is enough to support the view that there are different forces at play in the two markets.

I report the correlation between the first PC calculated from weekly changes in bond and CDS spreads and weekly changes in global variables such as VIX index and 5-year CDS on major banks on a rolling basis in Figure 1.5. Correlation in each window is based on approximately 2 years long sample (113 observations). Almost everywhere, the correlation between the first PC of CDS and these two global variables is higher than that between first PC of bond spreads. Average correlation of the PC of CDS changes with VIX is ~ 0.75 during the crisis and ~ 0.6 afterwards. Other studies have also reported high correlation of credit spreads with VIX.

The above patterns of comovement in CDS versus bonds support the view that systematic deviations in basis are driven by marginal investors in each market who respond differentially as global market conditions change. Thus, this section motivates examining the time series variation of the basis in response to global risk factors in the following section.

1.6 Empirical results: EM basis and US interest rates

Reaching for yield predicts a positive relationship between the US interest rate and EM basis. In this section I provide empirical evidence that support this hypothesis. I use a time series regression to test whether the changes in US yield curve level and slope can significantly explain the changes in basis, after controlling for global market conditions. Next, to argue that the effect of the US rates on basis is causal in nature, I use an event study approach with the FOMC meetings and study how the basis

responds to monetary policy announcements. Below I discuss the analysis and the results in detail.

1.6.1 Time series analysis

For a remaining maturity τ , basis is computed as

$$basis(\tau) = c(\tau) - (ytm(\tau) - OIS(\tau))$$

where $c(\tau)$ ($OIS(\tau)$) is the CDS (OIS) interpolated to match the remaining maturity of the yield, which varies between 3 to 5 years. The time series specification regresses changes in basis on the two key variables of interest, namely changes in the level and slope of the US yield curve, while controlling for other global variables. The choice of the control variables are motivated by a number of earlier studies that explore the effect of global market conditions on EM spreads. Although arguably there is no a priori reason why such macroeconomic conditions will affect the basis, I entertain the possibility that they can differentially impact the CDS and bond markets, at least temporarily. So I include these variables, even though detailed interpretation of those coefficients is not the focus of this study.

Baseline regression

The baseline regression in average weekly changes with no lags is given below.

$$\begin{aligned} \Delta basis_t(\tau) = & \alpha + \beta_1 \Delta OIS3month_t + \beta_2 \Delta (UST10y_t - OIS3month_t) \quad (1.1) \\ & + \beta_3 \Delta (LIBOR3month_t - OIS3month_t) \\ & + \beta_4 \Delta (OIS3month_t - UST3month_t) \\ & + \beta_5 \Delta VIX_t + \beta_6 \Delta bankCDS5y_t + \beta_7 MSCIret_t + \epsilon_t \end{aligned}$$

where $\Delta basis_t = \frac{1}{no.of.countries_t} \sum_{country\ i} (basis_{i,t} - basis_{i,t-1})$

Columns (1) and (3) in Table 1.3 report the results for the conventional and unconventional period respectively. Columns (2) and (4) report the results for the specification augmented with 4 lags of the regressors to capture reversal effect, if any. Inclusion of lags beyond 4 periods neither improves the adjusted R squared of the regressions nor change the sum of the lagged coefficients much. Newey-West standard errors with 2 lags are reported for each regression.²⁰

The *search for yield* hypothesis is when US interest rates fall there is a greater appetite for higher-yielding risky assets like EM debt instruments. Thus, the key variables of interest are the level and slope of the US yield curve, measured here by OIS3month and UST10y minus OIS3month respectively. There is little theoretical guidance whether the short rate (level) or long rate (slope) is relevant for reaching for yield. Existing empirical studies have used both; for example, *Eichengreen and Mody* (1998) uses 10 year US treasury rate while *Kamin and Von Kleist* (1999) suggests 3 month and 1 year treasury rates better capture the monetary policy stance as longer rates may be affected by inflation expectations. *Gilchrist et al.* (2014) uses 2 year treasury to capture the ‘path surprise’ in US monetary policy, and *Arora and Cerisola* (2001) uses the federal funds rate as a direct measure of monetary policy in their analysis. Without a priori assumptions, I explicitly include both the short and long rates in my time series regression and test for their significance.

For both pre and post period, the contemporaneous coefficient on the slope is positive and significant and suggests $\approx 36-46$ bps increase in basis when slope increases

²⁰Alternative specifications such as using a country fixed effects model with standard errors clustered by countries slightly affects the magnitudes of the coefficients but not the signs or significance of the coefficients. The qualitative results don’t change if daily or semi-weekly data is used instead of weekly data. Using 3 month US treasury as level and 10 year US Treasury minus 3 month US treasury as slope does not affect the main coefficients.

by 100 bps. The contemporaneous effect of the short rate is significant only in the pre period and the magnitude varies between $\approx 35-75$ bps for every 100 bps change in the level depending on the regression specification. The effect of the short rate is insignificant in the post period and is not surprising given little variation in the short rate post crisis. Overall, the positive coefficient is consistent with reaching for yield by global investors. When rates fall, investors increase their risk exposure in an attempt to earn higher returns. But since investing in risky assets like EM debt is easier through CDS, the demand pressure to sell CDS shows up as a downward movement of the basis.

The coefficient on the first lag of the slope is negative and indicates a reversal in the following week but not enough to offset the initial positive effect. This partial reversal could be attributable to the illiquid nature of the bond market which may cause it to react slowly to changes in macroeconomic conditions. For example, when the interest rate rises, if the bond yield does not change, the bond spreads declines because of the movement of the risk free rate. This then leads to a mismeasurement of the basis contemporaneously and hence the positive contemporaneous coefficient. But the negative lagged coefficients in the regressions imply that this effect, if there, corrects in the following week as the yields adjust. So even accounting for the slow reaction of bonds, the sum of the coefficients at t and $t-1$ show that the basis change is positive when interest rates rise which is consistent with the reaching for yield hypothesis. The sum of all lagged coefficients indicate the change in basis is temporary and reverses within 3-4 weeks. This is possible if arbitrageurs step in to close the widening gap in basis.

The coefficient on the other state variables in Table 1.3 are meaningful and in line with previous works on corporate basis (*Fontana (2011)* and *Bai and Collin-Dufresne (2013)*). 3 month Libor-OIS spread, VIX and 5y CDS for top banks are considered

proxies for funding risk in this literature and is expected to have a negative relationship with basis. That is, when short term inter bank credit/liquidity/volatility risk is high, the basis widens as illiquidity in the bond markets becomes more severe. A rise in Libor-OIS spread, VIX (indicator global risk aversion), or CDS spreads of top banks (health of dealers), implies tighter credit conditions which in turn contributes to deteriorating liquidity in bonds compared to CDS. I find the lagged sum of coefficients on these variables to be negative as expected (with the exception of bank CDS in the pre period). However, the contemporaneous coefficient on VIX and top bank CDS is positive and significant. This is possibly related to the faster reaction in the CDS markets compared to the bond markets. This is also consistent with the findings reported earlier using PCA; the first PC in the CDS market is more correlated with VIX than the first PC in the bond market. The coefficient on the short-term liquidity premium given by OIS3m-UST3m is mostly insignificant. I also include the average EM stock returns from MSCI as a control. The lagged sum of coefficients is insignificant in pre period but negative in post period. Stock returns are negatively correlated with credit spreads. But equity is more correlated to CDS market than bonds (*Longstaff et al. (2011)*) which could be possible given faster assimilation of information in both markets compared to bond market. This can explain why the contemporaneous effect of returns on basis is negative.

Rolling Regressions

In order to examine if the positive effect of the interest rates (level and slope) on the basis is robust across time, I run the regressions as before for rolling windows with 113 weeks (slightly over 2 years) of data. Panels in Figure 1.6 plot the estimated beta coefficients on each regressor for the specification excluding lags (Eq (1.1)) against

the last day of each window. The dotted line gives the 95% confidence band for the estimates where Newey-West standard errors with 2 lags are used. The results are similar to Table 1.3. The slope coefficient is positive and significant throughout the sample except for a short while during the early part of the crisis. The level coefficient is positive and significant until the latter part of the sample which is expected given the short rates were essentially stuck at zero post crisis. The signs of the funding cost proxies like Libor-OIS, VIX and bank CDS 5y are robust across time but the significance varies. Notable among these periods is VIX becoming significant in explaining the basis deviations during the crisis when VIX levels were at a historical high.

Figure 1.7 plots the sum of all the coefficients (contemporaneous and 4 lags) for each regressor along with the 90% confidence interval. The bands are computed using the estimated variance-covariance matrix of the estimated coefficients in the regression with 4 lags. The sum of contemporaneous and lagged coefficients is mostly insignificant which implies the reversal of the effects.

1.6.2 Basis Reaction around FOMC meetings

To capture the effect of monetary policy on the EM sovereign CDS-bond basis, I follow *Hanson and Stein (2015)* and *Gilchrist et al. (2014)* and use changes in 2-year nominal treasury rate around the Federal Open Market Committee (FOMC) announcements as a proxy for monetary policy news about expected medium path of interest rates. FOMC announcements communicate news about both the level of the target federal funds rate and the expected path of the federal funds rate over the next quarters. But post crisis, the latter became the primary content as the target lingered close to zero.²¹

²¹For further discussion of the *target surprise vs path surprise* in US monetary policy, see *Gurkaynak et al. (2005)*, *Hanson and Stein (2015)*, *Gertler and Karadi (2015)*, and *Gilchrist et al. (2014)*

Effect of FOMC announcement on the CDS-bond basis

The FOMC announcements are usually made 8 times a year. The calendar is pre announced on the Federal Reserve website. During the conventional period (1/1/2004 to 11/24/2008) there were 41 announcements and during the unconventional period (11/25/2008 to 11/14/2014) there are 50 announcements. In both periods there were two inter meeting dates.²² I computed 2-day changes in the CDS or yield spreads for each country first and then averaged the changes over the number of available countries.

I run the following baseline regression specification to estimate the effect of FOMC announcements on the basis. The sample size is 40 in the conventional period and 50 in the unconventional period.

$$\Delta_{t-1,t+1}basis = \alpha_1 + \beta_1\Delta_{t-1,t+1}UST2y + \eta_{t+1} \quad (1.2)$$

where $\Delta_{t-1,t+1}X$ denotes a 2 day change in variable X from t-1 to t+1 bracketing the FOMC announcement at t. If we could interpret the coefficient β_1 as the effect of change in monetary policy stance on the EM CDS-bond basis, then a positive coefficient will be consistent with investors reaching for yield, that is, when interest rates are lowered, yield oriented investors create a selling pressure in CDS market, thereby lowering the basis. I estimate Eq (1.2) using ordinary least squares with robust standard errors. The result is reported in Panel A of Table 1.4.

Possibility of reverse causality makes the above interpretation of β_1 problematic.

²²Inter meeting dates in the conventional period were 22-Jan-2008 and 8-Oct-2008 and in the unconventional period were 25-nov-2008 and 1-Dec-2008.

To address this concern, I run the following regression.

$$\begin{aligned} \Delta_{t-1,t+1}basis &= \alpha_2 + \beta_2\Delta_{t-1,t+1}UST2y + \delta FOMC_t \\ &+ \gamma FOMC_t \times \Delta_{t-1,t+1}UST2y + \epsilon_{t+1} \end{aligned} \quad (1.3)$$

where FOMC equals 1 for FOMC announcement days and 0 otherwise. This specification uses 2-day changes (t-1 to t+1) in basis for each day (t) in the sample, and includes the interaction between the changes in UST2y and the FOMC announcement dummy in the regressions. I estimate Eq (1.3) using OLS with Newey-West standard errors with 10 lags (equivalent of 2 lags used in the weekly setting). Results are reported in Panel B of Table 1.4.

β_1 is estimated to be 0.249 and 1.425 in the conventional and unconventional period respectively but it is only statistically significant at 1% in the unconventional period (Panel A in Table 1.4). The magnitude implies 100 basis point increase in UST2y over two days around the FOMC announcement, raises basis by 143 basis points in the unconventional period. There are two possible concerns with this interpretation.

First, reverse causality implies Fed might be responding to some macro information that is contained in the movement of the basis. For example, the Fed may lower rates in response to diverging basis which is an indication of malfunctioning credit markets. Although this is more likely to be true only in emergency situations like the crisis in 2008, in general, it is unreasonable to assume that the regular FOMC announcements responds to movements in high frequency changes in basis. If the reverse causality is due to some unobserved variable driving the correlation between US rates and the basis, the reaction of basis on FOMC and non-FOMC days should not be different i.e, the interaction term should not matter. In the unconventional period, the interaction

coefficient is 0.724. This is economically large and implies effect of 100 bps increase in interest rate on basis on FOMC day is nearly 143 bps , twice as much on the non-FOMC day which is about 70 bps.

Second, does the interest rate change during these announcements represent Fed’s private macro news rather than monetary policy stance? *Hanson and Stein* (2015) argue that on non-FOMC days, the changes in UST2y are representative of macro news than monetary stance of the Fed. If on FOMC announcements only macro news is revealed, then the coefficient γ should not be significant. The economically significant estimate of the interaction term suggests FOMC days have information about policy stance beyond the macro news which is prevalent on other days.

The evidence in Table 1.4 shows the sensitivity of EM sovereign basis in response to the *path* surprise in US monetary stance conveyed at FOMC announcements and proxied in the literature by changes in UST2y rate. The effect is present in both conventional and unconventional period although it is stronger post crisis.²³

Horizon dependence

The next question is how horizon dependent are these estimates. This is relevant given the concern of potential illiquidity in EM sovereign bonds. I estimate the following regression for h- day change in basis where h=1,2,...,5.

$$\Delta_{t-1,t+h}basis = \alpha + \beta\Delta_{t-1,t+1}UST2y + \eta_{1,t+1} \quad (1.4)$$

Figure 1.8 plots the estimated β against the horizon h - an impulse response of

²³Table 1.16 and 1.17 in the Supplementary Results reports the response of 2-day change in CDS and yield spreads to 2-day change in UST2y. The elasticity of CDS spread to 2 year treasury is 0.183(1.049) on FOMC days during the conventional(unconventional) period. In comparison, the elasticity of YS spread to 2 year treasury is -0.08(-0.45) on FOMC days during the conventional(unconventional) period.

basis over h days to -100 bps change in 2-year Treasury over 2 days around the FOMC announcement. The slight reversal of the basis is seen in both the conventional and unconventional period, although the initial impact is both greater and significant in the unconventional period.²⁴ This adjustment in the basis is likely due to the illiquid nature of the underlying bond market. This is further illustrated in Table 1.5.

Table 1.5 presents the OLS estimates of 2-day ($h=1$) and 6-day ($h=5$) change in the components of the basis, namely CDS and YS (yield spread), in response to 2-day change in UST2y on FOMC days. Robust standard errors are reported in each case.

The first row in both panels shows that the direction of the CDS changes and the YS changes are opposite. In fact, the estimates for 2-day YS changes are insignificant in both conventional and unconventional periods. But when the change is measured over 6 days bracketing the announcement, the coefficient on YS change changes from -0.8 to 0.357 in the conventional period. The corresponding change is -0.45 to -0.08 in unconventional period. This could be because the bond yields take more time to react to the FOMC news. As a bit of supporting evidence, in the last column, I report the estimated response in EM bond yield from *Gilchrist et al.* (2014). I compare this with the response of the bond yields given in the column (4). Even though sample size, number of EMs and the measure of monetary surprise in *Gilchrist et al.* (2014) are different from my current analysis, the qualitative pattern of estimates are broadly similar.²⁵

The response in the yield spread (YS), when measured over a longer span, follows that of the CDS, which lends support to the illiquidity story. However, it is important to note that the economic magnitude of the change in basis, 5 days after the announce-

²⁴Figure 1.19 shows the impulse response of the basis and its components over the horizon without the confidence bands.

²⁵*Gilchrist et al.* (2014) estimates are for speculative grade portfolio of EM bonds. Conventional period: 2/6/1992-11/24/2008. Unconventional period: 11/25/2008-4/30/2014

ment, is still large, particularly in the post crisis period which means that the slow reaction in yields is not enough to explain the movement of the basis following FOMC announcements. In fact, the change in the basis is driven by movement of the CDS; in the unconventional period, the CDS falls by ≈ 107 bps after 5 days in response to -100 bps change in UST2y while the movement in the yield spread is negligible.

Robustness to other proxies of US monetary policy

For robustness checks, in Table 1.6 I report the results of a specification similar to Eq (1.2) except that it uses different variables as proxy for the monetary policy. A few patterns emerge from this analysis which strengthen the results presented already. a) Overall, the sign of the coefficients are positive which is consistent with reaching for yield (except for 3 cases - OIS3m, UST3m, UST10y-UST2y in conventional period). b) The economic magnitude of the coefficients in the unconventional period is larger than the conventional period. This could be because dealers/arbitrageurs are more constrained in the post period, thereby, intensifying the impact of CDS selling. c) The coefficient on the slope of the US yield curve proxied by UST10y-OIS3m varies between 0.205 to 0.527 on FOMC days compared to 0.376 to 0.455 in the multivariate specification in Table 1.3. But the coefficient on the level of the US yield curve proxied by OIS3m is not comparable to the estimate in Table 1.3, possibly because target surprise on FOMC days is insufficient to capture the future path of monetary policy. On a similar note, UST2y changes explain more variation in the changes in basis than shorter term rates like UST3m or OIS3m. This lends support to using UST2y rates to capture the *path* surprise of monetary policy.

1.6.3 Effect of quantitative easing related announcements on basis

“ Thus, our purchases of Treasury, agency debt, and agency MBS likely both reduced the yields on those securities and also pushed investors into holding other assets with similar characteristics, such as credit risk and duration. For example, some investors who sold MBS to the Fed may have replaced them in their portfolios with longer-term, high-quality corporate bonds, depressing the yields on those assets as well.”

—Ben Bernanke Speech, 27 Aug, 2010

With the funds rate at zero lower bound during the unconventional policy regime, the FOMC conducted monetary policy by altering the size of the Fed balance sheet. Studies such as *Krishnamurthy and Vissing-Jorgensen* (2011) have shown that the easing policies of the Fed affected asset prices in US. Here we extend the empirical analysis to examine how the QE related announcements impacted the EM CDS-bond basis.

Description of the QE announcement data

Table 1.7 gives a brief description of the QE related announcement. The dates until 3 Nov, 2010 are based on dates used in *Fratzscher et al.* (2016). I add important Fed announcements dates after 3 Nov, 2010 based on official Fed reports and media articles. I also select a subset of these QE dates for a cleaner indicator of changes in expected long term rates in US. Following the literature, I exclude a) 1 Dec,2008 and 10 Aug, 2010 because other major news that could impact the market were also announced on these dates b) 2009 phase out dates because they were found to be largely irrelevant for market. In the post 2010 period, I exclude the dates if the Fed announcement stated that they will continue to follow their current policy without any new changes. In the end 12 announcements are selected out of 19 in total (Excluded dates are highlighted

in Table 1.7).

Basis change on QE announcement days

For the event-study, I define two categorical variables, $event_{1t}$ and $event_{2t}$. Both take value -1 if the QE announcement type is an expansion, 1 if phase out, and 0 otherwise. Expansion (phase out) is defined based on negative (positive) changes in UST2y around the selected announcements listed in Table 1.7. As shown below, $event_{1t}$ is based on 1-day change and $event_{2t}$ is based on 2-day change in UST2y.

$$1) \Delta_{t-1,t}basis = \alpha_1 + \beta_1 * event_{1t} + \epsilon_t \quad (1.5)$$

$$\begin{aligned} event_{1t} &= -1 \quad \text{if } \Delta_{t-1,t}UST2y < 0 \text{ on QE announcement}_t \\ &= 1 \quad \text{if } \Delta_{t-1,t}UST2y > 0 \text{ on QE announcement}_t \\ &= 0, \text{ otherwise} \end{aligned}$$

$$2) \Delta_{t-1,t+1}basis = \alpha_2 + \beta_2 * event_{2t} + \eta_t \quad (1.6)$$

$$\begin{aligned} event_{2t} &= -1 \quad \text{if } \Delta_{t-1,t+1}UST2y < 0 \text{ on QE announcement}_t \\ &= 1 \quad \text{if } \Delta_{t-1,t+1}UST2y > 0 \text{ on QE announcement}_t \\ &= 0, \text{ otherwise} \end{aligned}$$

Classifying expansion (phase out) using actual changes in UST2y is meaningful because market expectations prior to the announcements may have been different. For example, although the Fed announced possibility of greater expansionary measures on 1/28/2009, the UST2y rate increased, i.e. the market reaction (reflected in 1-day or 2-day change in UST2y) was not the same as the intended type of announcement. Table 1.8 presents the actual changes in UST2y and the slope on selected announcement dates.

Eq (1.5) and (1.6) are estimated for post crisis period with daily data. Estimates of β_1 and β_2 with Newey-West standard errors with 10 lags are reported in Table 1.9. Column (1) in Table 1.9 suggests that, on average, the basis fell by 14 bps on the day of an expansion announcement. Column (2) suggests the basis fell by 12.7 bps till day after an expansion announcement where expansion is identified by negative 2-day change in UST2y.

As seen in previous subsections, the change in basis reverses slightly in the day following the announcements, possibly due to adjustments in the illiquid bond markets. To show a similar pattern following the QE announcements, regression below estimates basis change over 1 to 6 days after the QE event defined as in Eq (1.6).

$$\begin{aligned} \Delta_{t-1,t+h}basis &= \alpha + \beta * event_t + \eta_t \quad \text{where } h=1,2,3,4,5,6 & (1.7) \\ event_t &= -1 \quad \text{if } \Delta_{t-1,t+1}UST2y < 0 \text{ on QE announcement}_t \\ &= 1 \quad \text{if } \Delta_{t-1,t+1}UST2y > 0 \text{ on QE announcement}_t \\ &= 0, \text{ otherwise} \end{aligned}$$

where $\Delta_{t-1,t+h}basis$ is the change in basis h-days after the announcement. Figure 1.9 plots the average basis change over the next days following QE announcement with 95% confidence interval. Change until 3 days after announcement horizon are significant at 5%.

The change in basis is driven by the response of CDS on QE announcement days, even after accounting for the slow adjustment in the yield spreads. Columns (1) - (5) in Table 1.10 report the average change in basis, CDS spreads, yield spread, yield and OIS respectively on the day of the announcement and on the day after the announcement. I find CDS spreads fall by ≈ 10 bps on expansion announcements and by 7 bps more on

the following day while the yield spread increases by ≈ 4 bps on announcement. Over the next day, the yield spread starts to follow the CDS movement but still the overall change is ≈ -3 bps ($=3.9-6.8$) which is small compared to -17 bps ($=-10-7$) change in CDS. This implies, even though that the yields are slow to change, the average change in basis is driven by change in CDS on announcement days.

Lower treasury rates cause the CDS spreads to fall on account of yield oriented investors selling more CDS. The resultant demand pressure leads to decline in the basis. I provide evidence in support of this claim from the aggregate CDS positions data in the following sections.

1.7 Evidence on CDS positions

This section studies the sovereign CDS buying/selling trend in the aggregate sovereign CDS market and for the largest mutual funds who invest in EM debt and shows that investors sell CDS in a manner consistent with reaching for yield.

1.7.1 Aggregate sovereign CDS sold and US yield curve

Aggregate data

I collate publicly available data on CDS positions reported in Depository Trust & Clearing Corporation (DTCC) website from Oct 2008 to July 2016. DTCC reports gross notional amount of CDS in USD equivalent for reference categories by type of buyer and seller of protection every week. The buyer and seller types are categorized as "Dealers" and "Non-dealers". For sovereign EMs, the most granular category of reference entity that is available publicly is "Sovereign/State Bodies". This is possibly an imperfect measure of only EM CDS. However, the volume of CDS for advanced

countries is expected to be smaller. Also, patterns in outstanding amount of CDS referencing smaller European countries such as Greece or Italy (if included in the DTCC data), arguably look much like EM in the post crisis era. DTCC defines *dealer* as any user that is, or is an affiliate of a user who is, in the business of making markets or dealing in credit derivative products; and *non-dealer/customers* as any user that is not a dealer and that uses the system to confirm eligible credit derivative transactions, primarily with dealers. These include institutions such as traditional asset management firms, hedge funds, insurance companies, etc. For each investor type (dealer or non-dealer), I calculate the net notional amount of CDS sold as the difference between the gross amount sold minus the gross amount bought by the particular investor type.

Patterns in sovereign CDS market

Figure 1.10 compares the gross notional amount of sovereign CDS with all types of CDS. Gross notional amount of sovereign CDS averages about 2.4 trillion USD over the sample period from end-2008 to mid-2016. This is less than one-tenth of the average gross amount for all CDSs combined. Total notional amount of all type of CDS has fallen from over 30 trillion in end-2008 to nearly \$10 trillion in mid-2016 while sovereign CDS market has been expanding from end-2008 to mid 2012 and then has been steadily falling. Figure 1.20 in Supplementary Results shows single-name CDS forms more than 90% of the sovereign CDS market unlike corporate, where market for CDS indices is almost as large as single-name market .

Figure 1.11 shows that the dealers' gross sovereign CDS position is much larger than non-dealers' position - average weekly notional amount of sovereign CDS position of dealers is \$2.1 trillion USD compared to \$0.3 trillion USD for non-dealers. Figure 1.21 in the Supplementary Results shows buying and selling activities of non-dealers

have steadily increased and therefore, have decreased for dealers since 2013. Figure 1.12 shows that non-dealers are net sellers of sovereign CDS since 2010 and the average net amount sold during this period is ~ 25 billion USD. This means the dealers are net buyers of sovereign CDS since 2010. *Siriwardane* (2016) also reports a similar decreasing trend of trading CDS in dealers in the US corporate CDS market.

Relationship between CDS net selling and slope of US yield curve

In Figure 1.13 I restrict the sample from Oct 2008 to Nov 2014 to keep it comparable with the sample of basis data used before. Top panel shows a strong negative correlation between net selling of sovereign CDS by the non-dealers and the US yield curve slope. Since there is a downward trend in OIS3m since the beginning of the sample, I remove the linear trend in OIS3m and plot net sovereign CDS sold by non-dealers and the detrended OIS3m in the bottom panel. The correlation between net selling of sovereign CDS and slope is -0.53 in my sample period of Oct 2008-Nov 2014. The correlation between net selling and detrended OIS 3m is -0.15 (without detrending, the correlation is -0.52). Both correlations are significant at 1% level. The time series behavior of net CDS sold and US yield curve level and slope support my hypothesis of reaching for yield via CDS selling - when the interest rates are low, investors are encouraged to sell more CDS in order to take risk in debt market. In fact, in unreported results, I verify that this strong negative relationship holds for all aggregated CDS types reported DTCC. This suggest investor behavior like reaching for yield is not specific to just the sovereign CDS markets.

Table 1.11 shows the result of regressing the weekly sovereign CDS changes on the exogenous global variables. The significant negative coefficient on the slope term indicates reduced selling when slope increases. The magnitude is significant economically

too - a 100 bps decline in the slope of the US yield curve implies investors (net)sell 3 billion USD of notional amount of CDS in a week and 4.5 billion USD notional amount over two weeks.²⁶ Comparison of contemporaneous coefficients between the regression result for changes in basis (Column (4)) and net CDS sold (Column (2)) shows opposite signs on all exogenous variables except the liquidity premium (OIS3m-LIBOR3m). This pattern is consistent with reaching for yield.

1.7.2 Largest mutual funds in EM CDS market

Recent literature on derivative usage among institutional investors finds mutual funds are one of the biggest players in the CDS markets. *Guettler and Adam* (2010) find that among largest 100 US corporate bond funds, not only the use of CDS increased from 20% to 60% between 2004 to 2008, but the size of the positions also increased manifold. This section provides evidence that largest mutual funds that invest in EM debt market take risk and lever-up via CDS. This makes sense as mutual funds are supposed to be liquid and CDS markets are more liquid than the bonds. *Aragon et al.* (2016) find, when faced with an outflow, bond funds sell fewer bonds if they are CDS users i.e, CDS usage helps them partly substitute selling the bonds with buying CDS to maintain a target risk level. However, using CDS requires some infrastructure, so the largest mutual funds (which usually belong to a fund family) are more likely to be users of CDS (*Guettler and Adam* (2010)).

Net flows to US mutual funds

Using monthly net assets and returns data for all US mutual funds that invest in emerging market debt (Lipper Class=EMD) from the Chicago booth CRSP Database

²⁶In unreported results using rolling windows, I find the net selling falls by 2 to 4 billion USD when slope increases.

for Jan 2006 to March 2016, I calculate the monthly net flow at fund level.²⁷ There are total 132 funds who have been classified as EMD at least once during the sample period. Figure 1.14 shows the concentration among these mutual funds by comparing the ratio of aggregate net flow to aggregate net assets of all these mutual funds with that of largest 17 funds. The plots are quite comparable in level and time series. It shows that I can focus on these selected funds in the following analysis without loss of generality.²⁸

The 17 largest funds are chosen such that a) they have the highest net assets in 2006m1, b) they invest primarily in EMD during the sample period (occasionally some of these funds are classified by Lipper as ‘HY’ (High Yield), ‘EML’ (Emerging Market Local), ‘CRX’ (Currency), or ‘INI’ (International Income) based on how they invest, but the most common classification is ‘EMD’), c) They have full data during 2006-2016, and d) they have at least 50 million USD of net assets in Jan 2006.

The vertical dotted line in Figure 1.14 denotes the ‘*taper tantrum*’ - the reversal in EM flows following Fed governor Ben Bernanke’s announcement of phasing out US asset purchases. The EMD mutual funds experienced about 4.5 billion USD outflow, about 56% of which was from the top 17 funds. *Koepke* (2015) documents withdrawal of about 73 billion USD from emerging markets equity and bonds by global investors in 2013, about half of which in May alone. The sharp fall in emerging market sector on expectations the Fed tapering its bond purchases in May 2013 is seen as unwinding of reaching for yield in the emerging markets (*Haltom et al.* (2013)).

²⁷CRSP reports returns and net assets at share class level. I calculate net flow for each share class within a fund as follows: $NetFlow_t = NetAssets_t - NetAssets_{t-1} * (1 + return_t)$. Then I aggregate the net flows and net assets for all share classes within a fund.

²⁸In Figure 1.22 in the Supplementary Results, I compare 24-month rolling standard deviation of aggregate net flows/net assets of all funds to that of the 17 largest EMD mutual funds. The standard deviation of the top funds are comparable to that of the total.

Evidence from the largest mutual funds' filings

Table 1.12 lists the 17 largest EMD mutual funds mentioned above and documents their net assets at the beginning and end of the sample in decreasing order of initial size. Many funds have grown massively over the decade, sometimes by more than 10 times (one exception is Pimco Emerging markets bond fund which is smaller in terms of net assets in 2016 than in 2006). The last 4 columns of Table 1.12 show the average CDS selling behavior of these funds during 2006-2016. The data on CDS positions of these mutual funds are obtained from quarterly filings of investment portfolio by these funds at the Securities and Exchange Commission (SEC) via N-Q and N-CSR forms. Both these types of forms are filed semi-annually but during different quarters in the year. This gives me a quarterly data for each fund from 2006 to 2016. I manually collect this data on all outstanding CDS bought/sold as of the reporting date in the filings. I only use the sovereign CDS (not corporate CDS) used by the funds in this sample which is representative of the CDS usage by EMD funds because sovereign CDS constitutes the bulk of their CDS investment portfolio. Next, for each fund in each quarter, I aggregate all outstanding positions on different reference countries to obtain the net notional amount of CDS sold.

The two largest funds in Jan 2006, namely GMO and PIMCO Emerging markets bond fund, are by far the largest sellers of sovereign CDS contracts, having sold, on average during a quarter, a notional amount of ~ 1.3 billion(GMO) or ~ 0.8 billion (PIMCO) USD. The net CDS sold by these two funds, on average, amount to nearly 40-50% of their respective total assets. This is large compared to the other funds in the sample who only occasionally sell as much e.g. JP Morgan and Payden in pre-crisis period or Federated during 2014-2016. Even among the top funds, there is a lot of variation in the CDS usage, both in cross section and time series. 6 out of these 17

major funds, namely Fidelity, SEI Institutional International, Fidelity Advisor, DWS, Mainstay and Legg Mason, do not report any CDS usage in the quarterly filings between 2006-2016. Among the rest who do, the usage varies a lot over time. Figure 1.15 shows the net CDS sold as a % of net assets for these funds over time.

Reaching for yield via CDS predicts a negative relationship between net CDS sold and the US interest rates. Table 1.13 reports the results of regression of quarterly changes in net CDS sold (as a % of net assets) on changes in the level and slope of the US yield curve, controlling for the same global variables used in earlier sections. Since I only have the SEC filings from 2006, the conventional period here covers a shorter duration than the previous analysis. To keep the unconventional period duration the same as before, I only include filings reported on or before 14 Nov 2014.²⁹ The coefficient on the slope is negative and significant. In terms of magnitude, there is a decline of \approx 1.5 percentage points in net selling by these major funds when US yield curve slope increases by 100 bps in the unconventional period. However, the slope coefficient is positive but insignificant in the conventional period. The level of the yield curve, measured by OIS 3 month is not significant in any of the period. This could be partly due to the low power of test in the post period when 3 month OIS was close to zero. Another possibility is that reaching for yield became a more pressing concern for mutual funds in the post crisis period.

Overall, I show that largest mutual funds that primarily invest in emerging market debt are net sellers of CDS although the magnitude of their CDS usage could vary extensively over time as well as in cross section. However, one must be cautious because this analysis does not give a complete picture of the CDS usage. a) It excludes the smaller mutual funds or those classified differently than EMD but invest in sovereign

²⁹The regression results in the unconventional period does not change even if I include all filings until March 2016.

CDS market. b) The data is reported quarterly as a snapshot in time, so any change in behavior in the intermittent period is not captured. In spite of these shortcomings, the CDS selling behavior of the largest EMD funds is similar that of the corporate bond funds in US in that they represent more than 50% of the market and are net sellers of CDS. Studies have found that corporate bond funds use CDS for gaining more return. Here, in addition, I show there exists an explicit negative relationship between the CDS sold as a % of the net assets and the US yield curve slope. Combined, these findings point at speculative trading in EM debt via CDS.³⁰

1.8 Further Discussions

Comparison with corporate basis

The overall time series behavior of the EM basis is not unique. It closely resembles the US corporate basis reported in *Bai and Collin-Dufresne* (2013) - the basis is slightly positive during the early sample period but turns quite negative during the crisis and remains below zero thereafter. Systematic violation in the no-arbitrage conditions indicates constrained intermediaries; for example, large deviations in the corporate CDS-bond basis during crisis driven due to costly financial intermediation are discussed in *Mitchell and Pulvino* (2012) and *Fontana* (2011), or persistent deviations in covered interest rate parity in the largest asset markets in the post crisis period are reported *Du et al.* (2016). The EM basis here deviate from fundamental no-arbitrage value in two aspects - a) temporary changes due to selling pressure, which I claim is consistent

³⁰The motives of investing in CDS and bonds could be many. For speculation about worsening credit worthiness of a sovereign, the investors could buy a 'naked' CDS or sell a bond. In case of hedging the credit risk or to make profits from a negative basis, one could buy both the bond and the CDS. Selling the CDS combined with short selling a bond is an unlikely strategy as short selling a bond is difficult. Thus, CDS selling is mostly indicative of speculative risk taking.

with reaching for yield, and b) average level of basis is persistently below zero post crisis, possibly due to tighter risk management of intermediaries post crisis. Figure 1.16 plots weekly levels of the CDS-bond basis for high-yield (HY), investment-grade (IG) and EM. HY and EM have a BBB rating while IG is AAA-rated. The basis data for US corporate debt is provided by the authors in *Bai and Collin-Dufresne (2013)*.

Reaching for yield in US corporate debt?

If reaching for yield refers to the investors' propensity to take more risk, my hypothesis that the basis is positively related to US interest rates should also hold for other riskier investments like high-yield corporate debt. In time series regressions of weekly changes of US high-yield corporate basis on changes of US yield curve slope while controlling for other market conditions, I find 100 bps increase in the slope is associated with ≈ 50 bps change in basis which is comparable to what I found for EM basis (≈ 42 bps). The coefficient is negative for investment-grade basis which is usually AAA-rated and not expected to be subject to the *appetite for risk*.

1.9 Conclusion

In this paper I present evidence of transmission of US monetary policy to EM debt market that is most consistent with reaching for yield. To do so I use deviations in the CDS-bond basis which is a novel way to overcome the concern that the main result is driven by changes in country fundamentals. I find that the EM basis declines when US interest rates fall and the magnitude is economically and statistically significant. The basis response to US interest rate is not easily explained by illiquidity of the underlying bond markets or overreaction in CDS markets or time varying investor/dealer capital

constraints. The time series pattern of the EM basis is also not unique; it is comparable to similar no-arbitrage relationships in other asset markets where limited arbitrage conditions hold.

I argue that search for yield by global investors in risky EM debt market explains the observed behavior in a very consistent way. To support my hypothesis, I first show that aggregate sovereign CDS selling negatively varies with US interest rates, and then complement the analysis by giving examples of a few specific mutual funds who do the same. One word of caution is that I only examine a limited sample of EMD funds, who may not represent other key CDS investors like hedge funds. But in light of the existing literature that investigates motives and means of CDS usage by institutional investors, the evidence here strongly suggests yield chasing.

Figure 1.1: Weekly level in annual percentage of average EM yield spread, CDS spread and basis for remaining maturity 3-5 years.

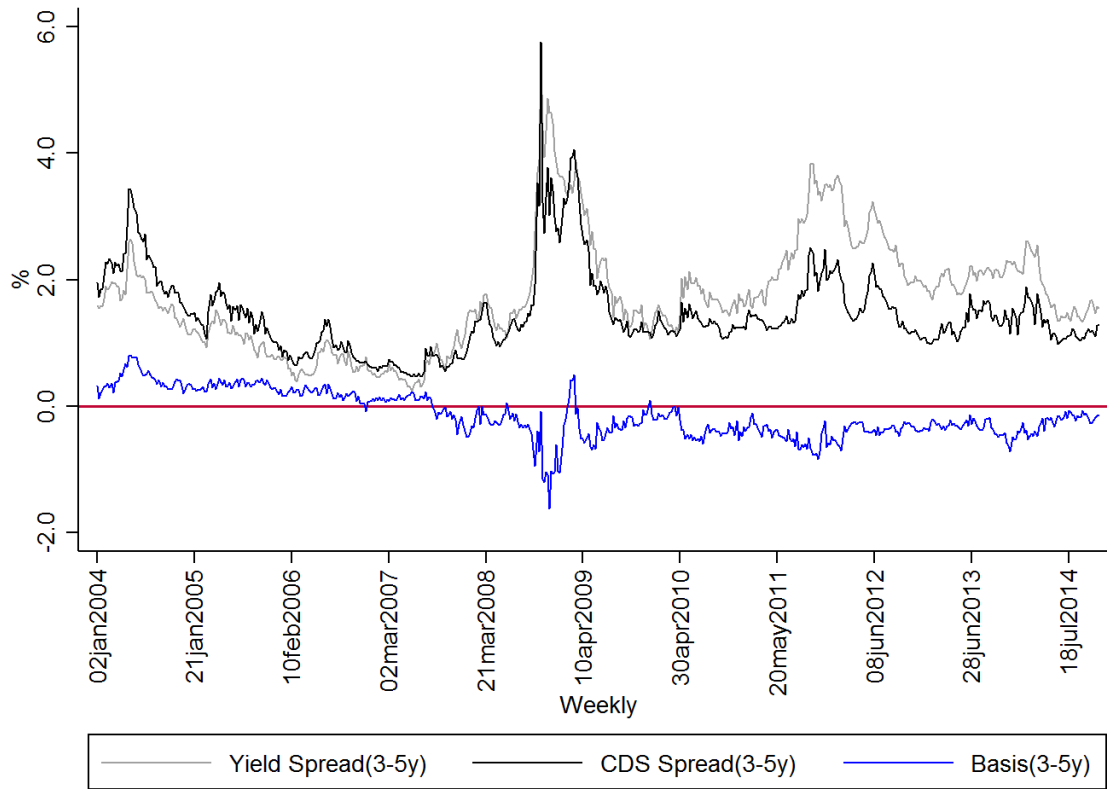
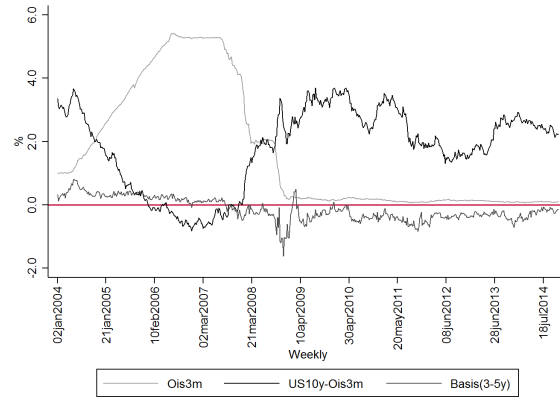
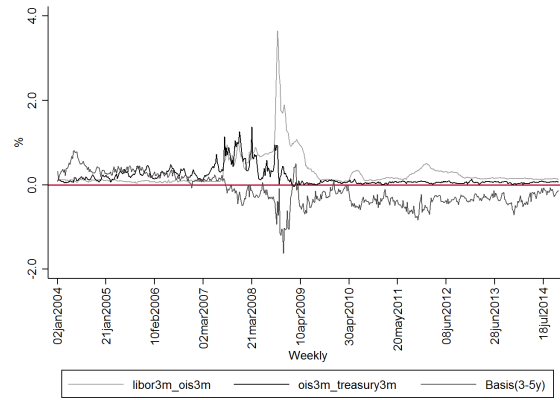


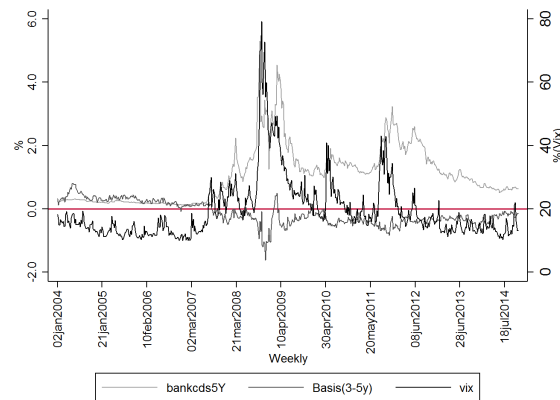
Figure 1.2: Weekly levels of average basis for remaining maturity 3-5 years and global variables.



(a) Level and slope of US yield curve



(b) Risk premium and liquidity premium



(c) VIX and bank health

Figure 1.3: Comovement in weekly levels of yield spreads and CDS spreads for 21 EM.

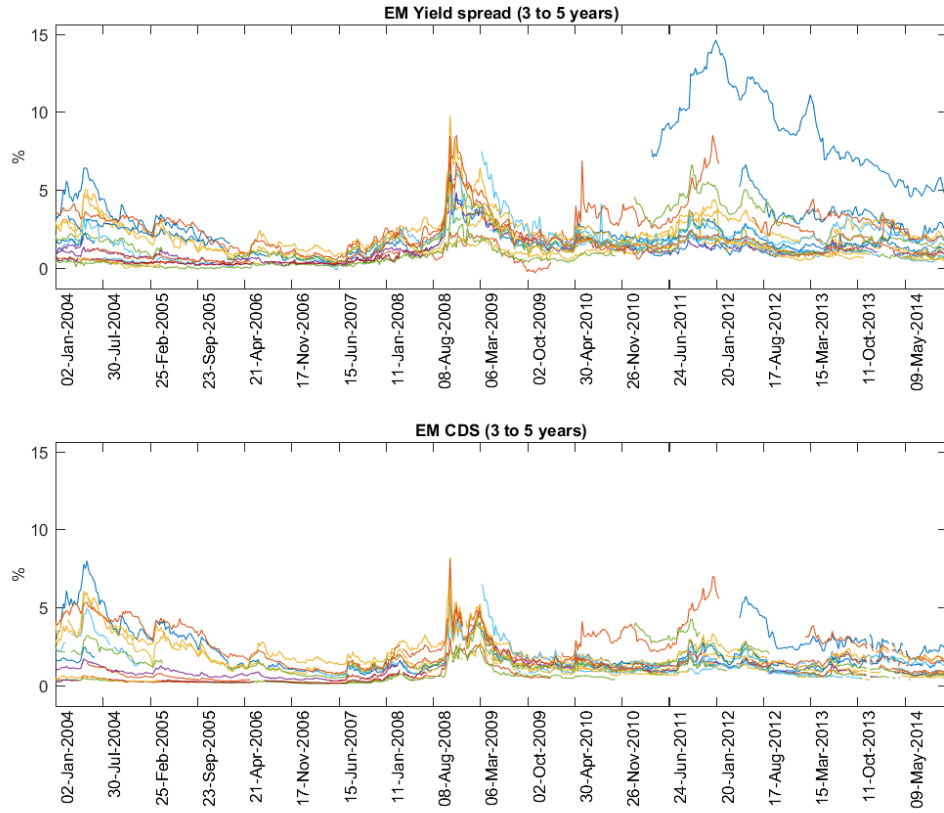


Figure 1.4: Percentage variation explained by the first principal component of 2-day or weekly changes in bond and CDS spreads on a rolling basis. Each window uses one-fifth of the total sample observations, T. For 2-day change data, T=1368 observations and window=273 observations. For weekly change data, T=567 observations, window=113 observations

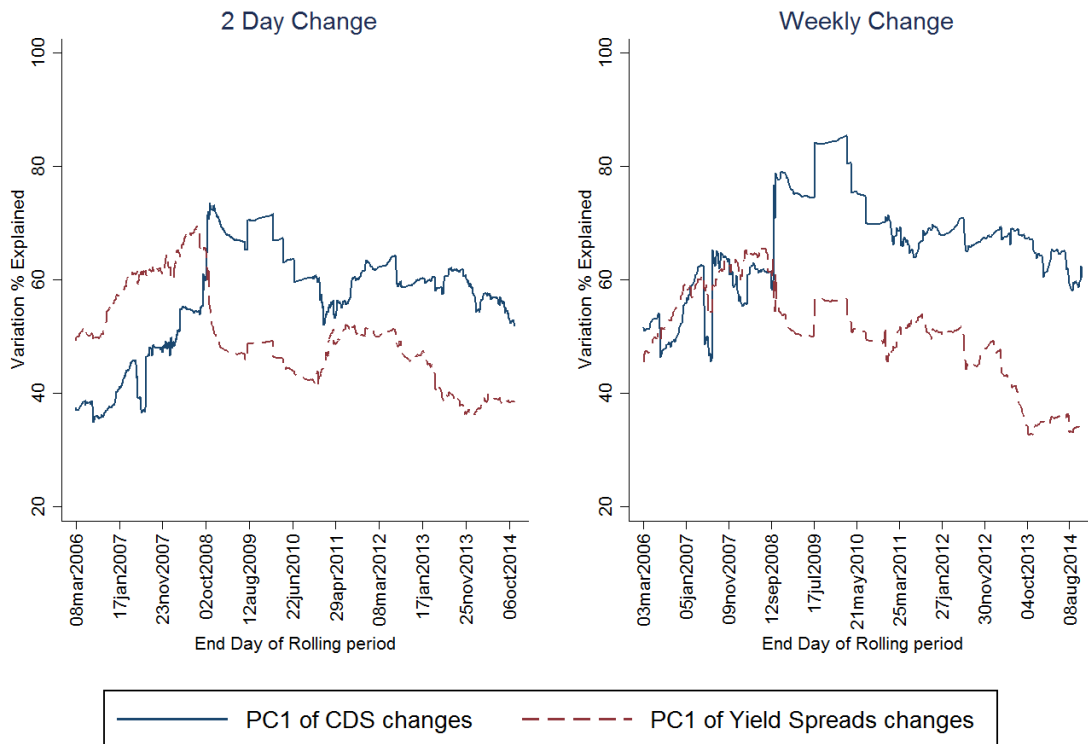


Figure 1.5: Correlation between the first principal component of weekly changes in bond and CDS spreads and weekly changes in global variables such as VIX and 5-year CDS on major banks on a rolling basis. Correlation in each window is based on 113 observations.

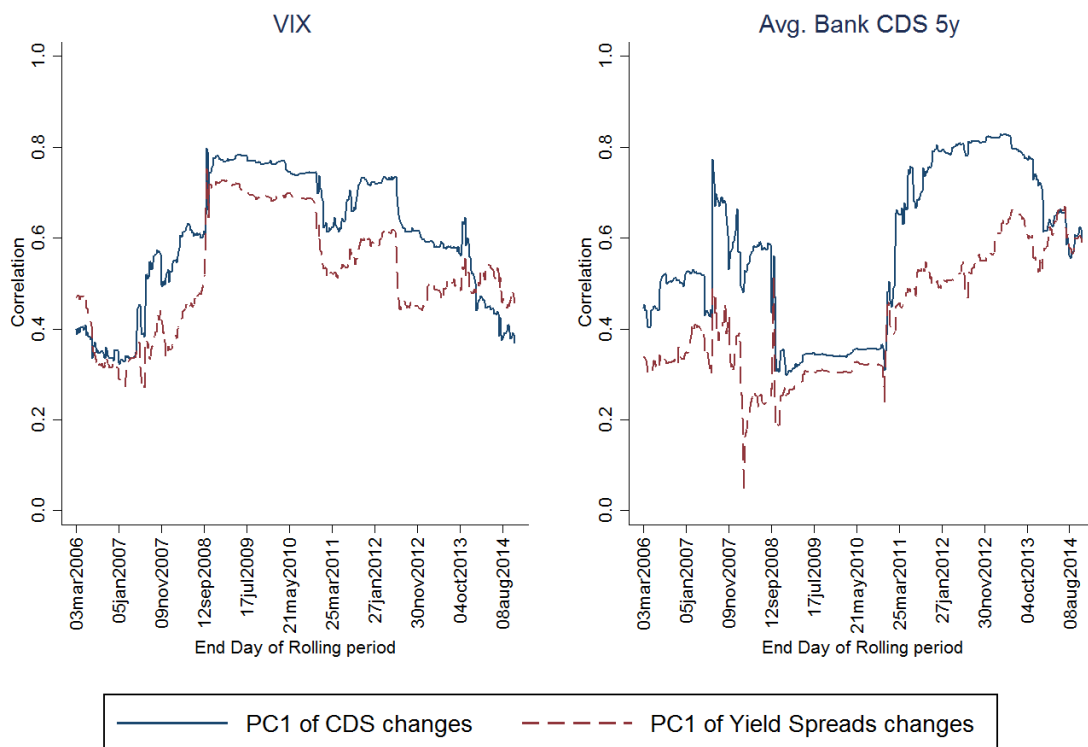


Figure 1.6: Rolling regression results for the baseline specification in Eq(1.1). Each panel plots the estimated coefficients on specific exogenous variables on a rolling basis. Each regression is estimated with about 2 year (113 weeks) of data. 95% confidence bands, calculated using Newey-West standard errors with 2 lags are shown.

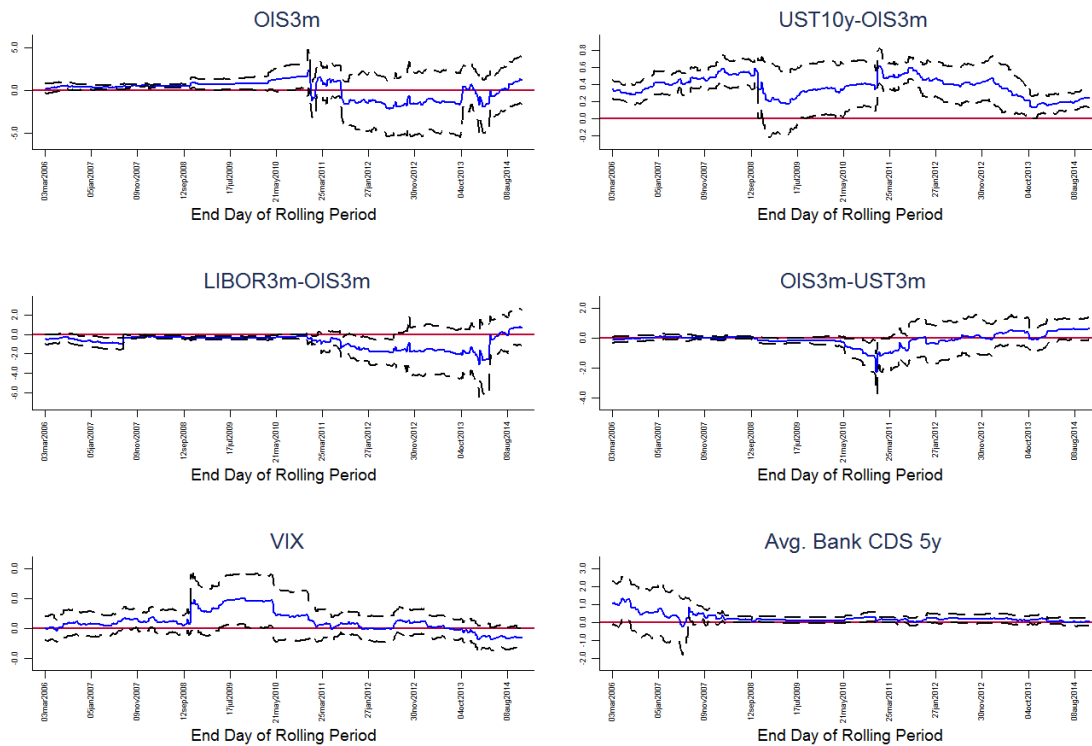


Figure 1.7: Rolling regression results for the augmented specification (baseline Eq(1.1) + 4 lags) are shown below. Each panel plots the sum of the estimated coefficients (t, t-1,..., t-4) on specific exogenous variables on a rolling basis. Each regression is estimated with about 2 year (113 weeks) of data. 90% confidence bands, calculated using Newey-West standard errors with 2 lags are shown.

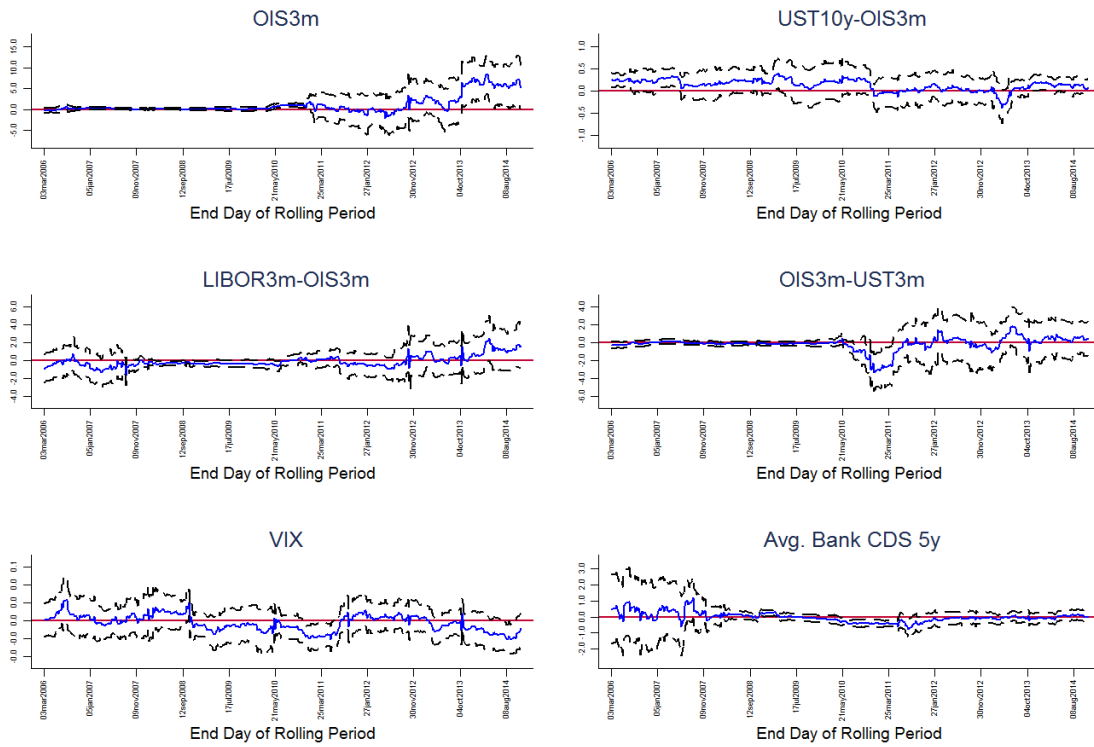


Figure 1.8: Impulse response of the basis (in bps) over 1,2,...,5 days to -100 bps change in UST2y over 2 days around the after FOMC announcements. Plot shows OLS estimate of β in Eq (1.4) against the horizon h . 95% confidence bands constructed with robust standard errors are shown.

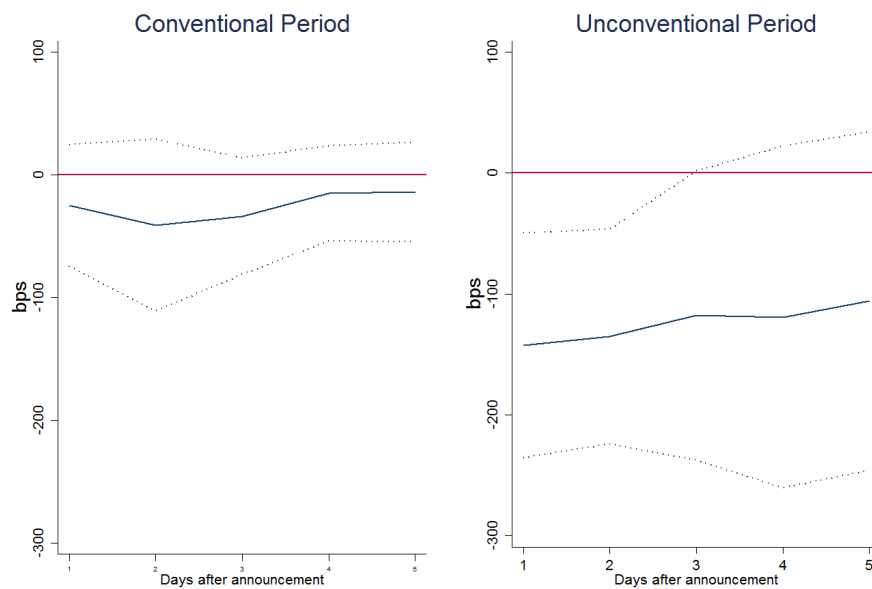


Figure 1.9: Change in the basis (in bps) over 1,2,...,5 days following a QE expansion where QE expansion is defined by negative 2-day change in UST2y on QE announcement. Plot shows the coefficient β in Eq (1.7). Newey-West standard errors with 10 lags are used to calculate the 95% confidence interval.

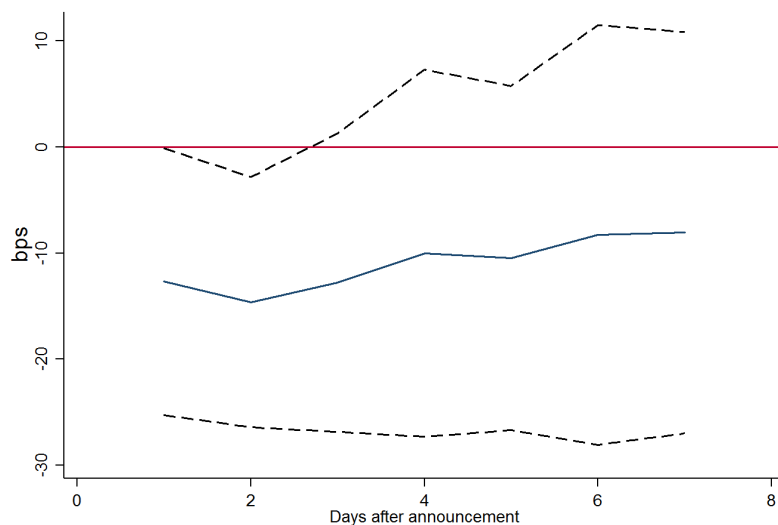


Figure 1.10: Comparison of weekly levels of gross notional sovereign CDS with all types of CDS.



Figure 1.11: Gross notional amount of sovereign CDS bought and sold by investor type. The top figure reports gross amount bought and sold by the non-dealers and bottom figure shows the same for dealers.

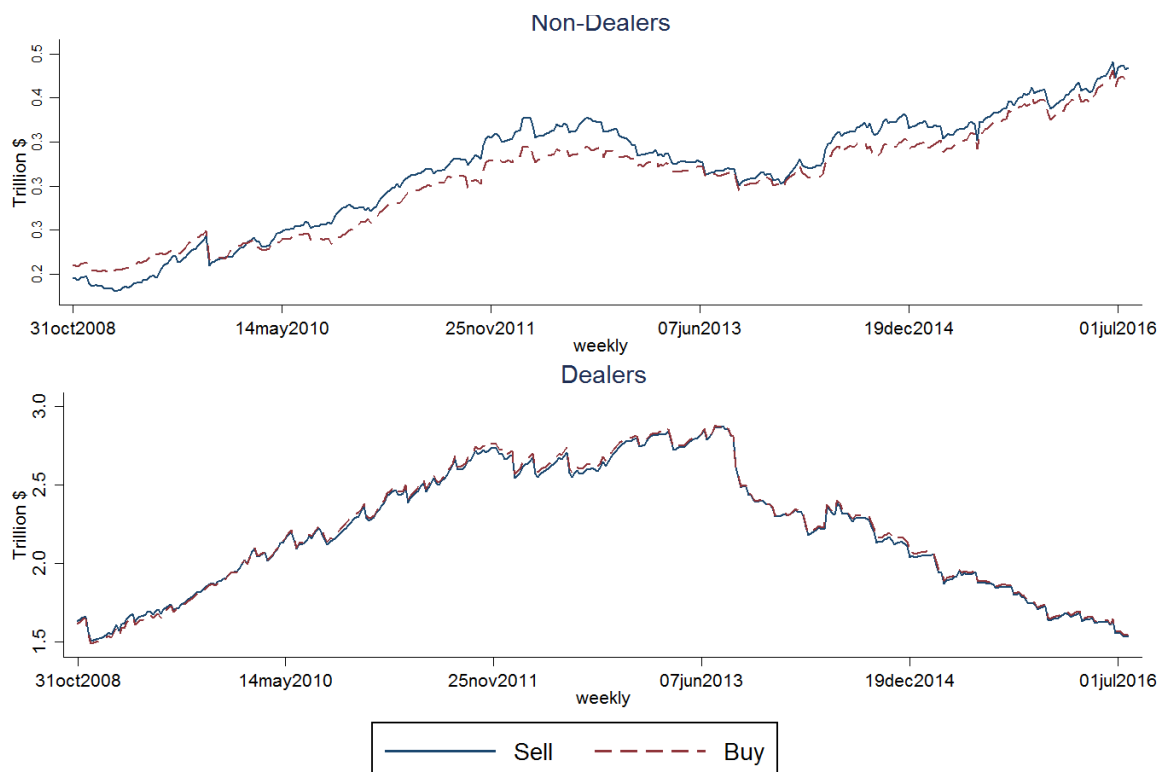


Figure 1.12: Net notional sovereign CDS sold by non-dealers.

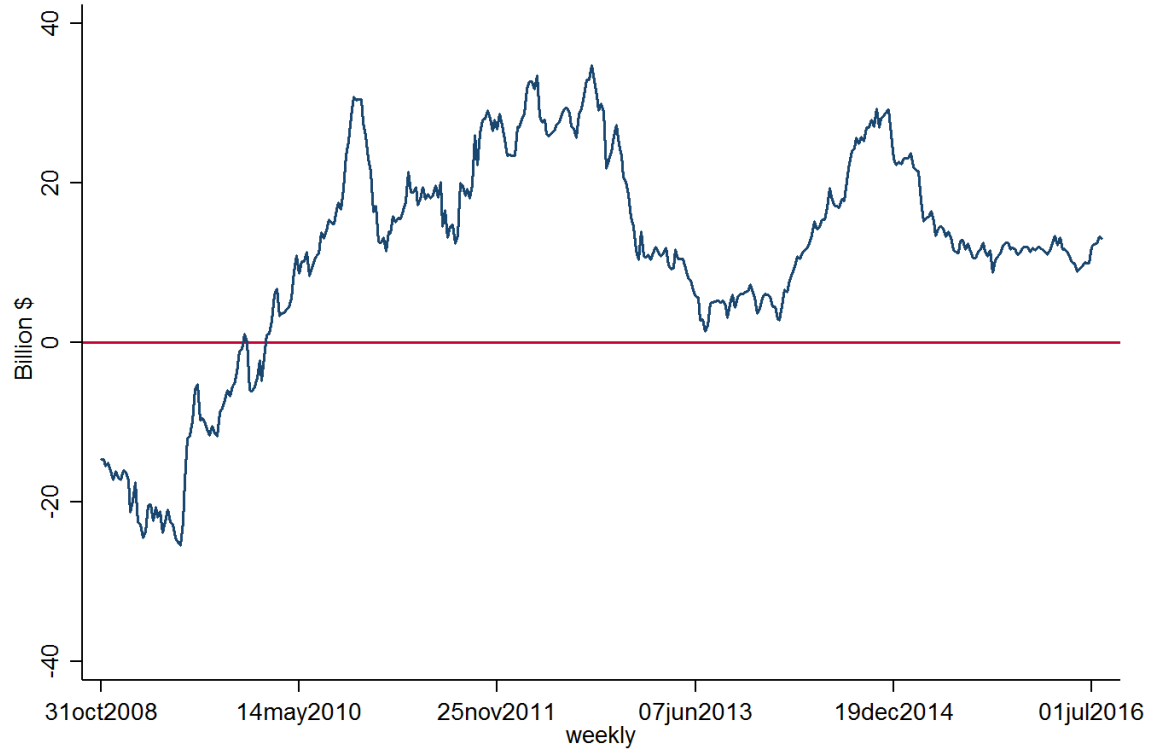


Figure 1.13: Time series variation of of US yield curve level (OIS3m) and slope (US10y-Ois3m) and net selling of sovereign CDS by non-dealers. Since there is a downward trend in OIS3m since the beginning of the sample, the series has been detrended using a linear trend. No trend correction is made for the slope. The figure consists of two line charts. The top chart, titled 'Net Sell Sovereign CDS and UST10y-OIS3m', plots 'Net Selling' (solid blue line, left axis, Billion \$) and 'UST10y-OIS3m' (dashed red line, right axis, % (US10_ois)) from 31oct2008 to 10oct2014. The bottom chart, titled 'Net Sell Sovereign CDS and OIS3m(Detrended)', plots 'Net Selling' (solid blue line, left axis, Billion \$) and 'OIS3m(Detrended)' (dashed red line, right axis, % (ois3m)) over the same period. Both charts show a general upward trend in net selling and a downward trend in the slope/yield curve level over the period.

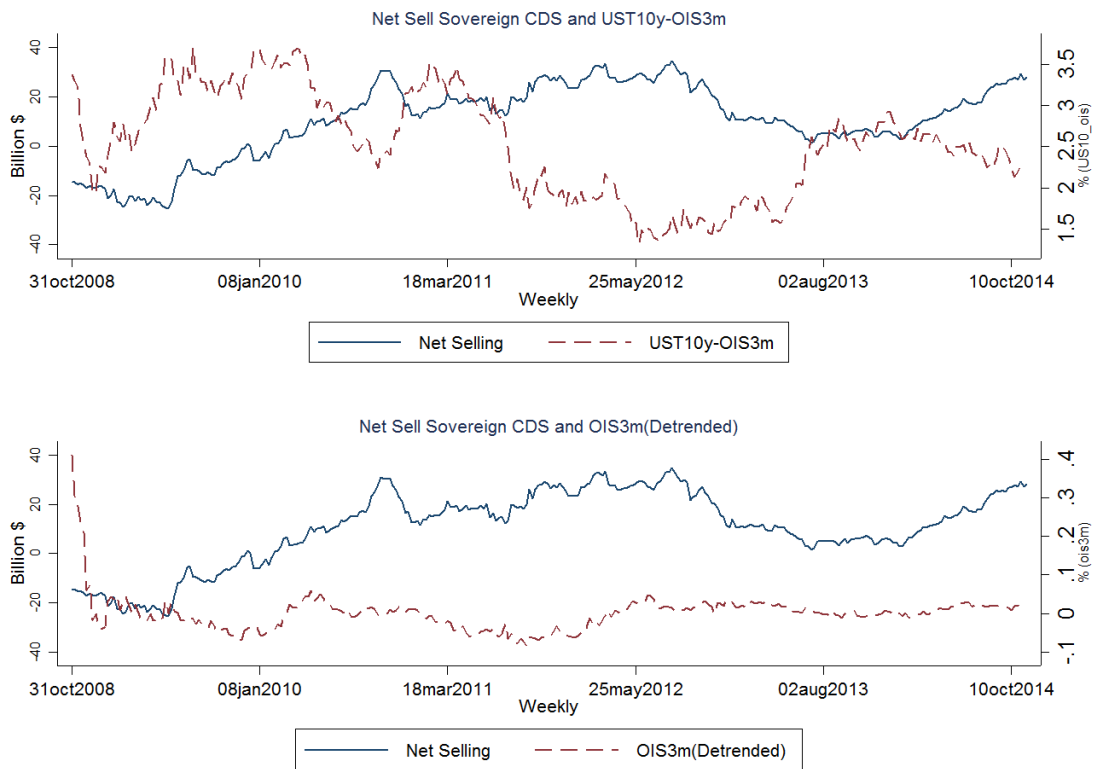


Figure 1.14: Compare monthly time series of aggregate net flow/ net assets between all mutual funds who invest in EM debt and 17 largest (as of Jan 2006) EMD mutual funds with complete data from 2006-2016

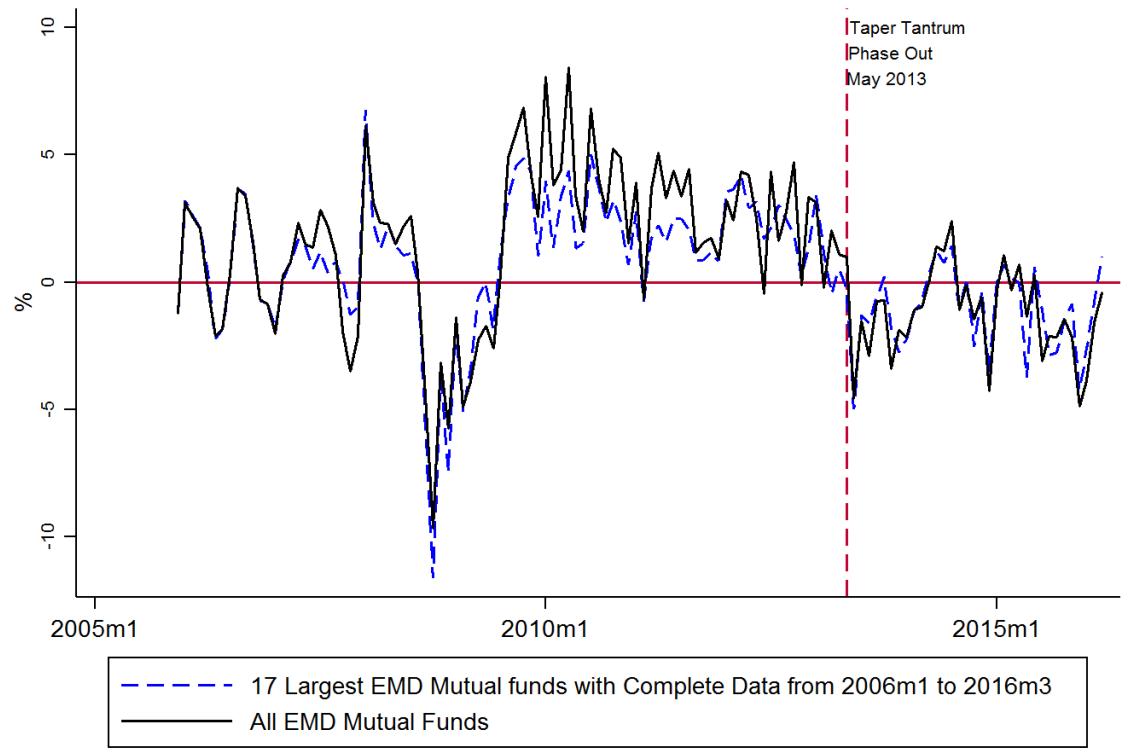
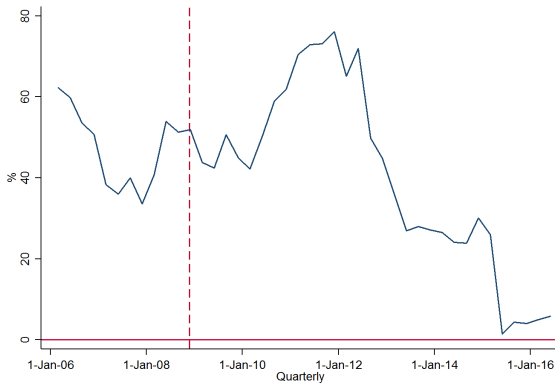
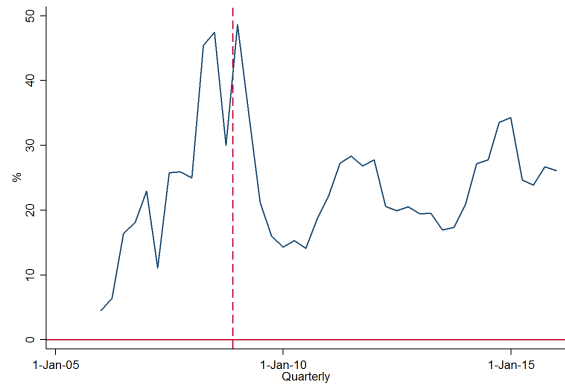


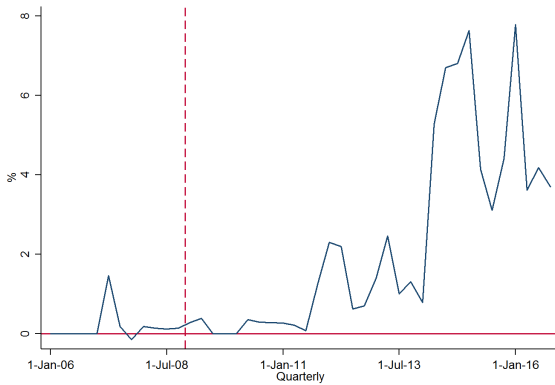
Figure 1.15: The panels below show quarterly time series of net CDS sold as a % of net assets for major emerging market debt mutual funds listed in Table 1.12. 6 out of 17 funds that do not have any CDS outstanding during the reporting period from 2006-2016 are excluded from panels below.



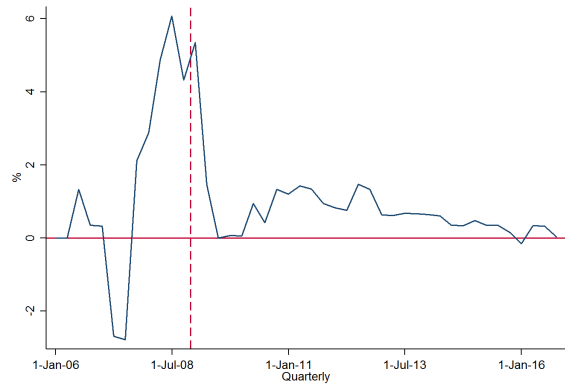
(a) GMO



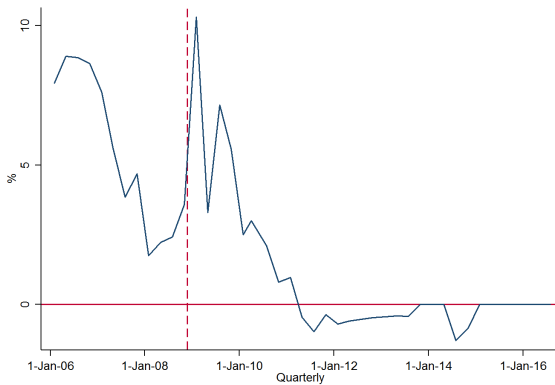
(b) PIMCO



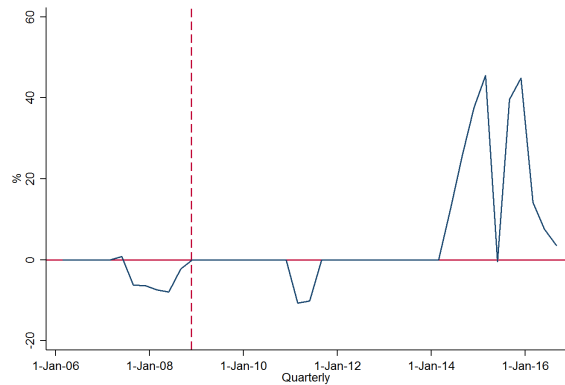
(c) PIMCO LOCAL



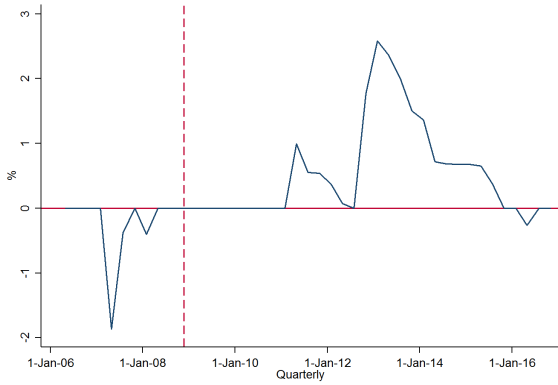
(d) TRowe



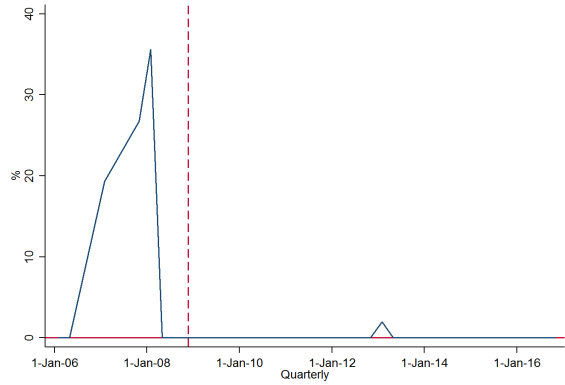
(e) Alliance



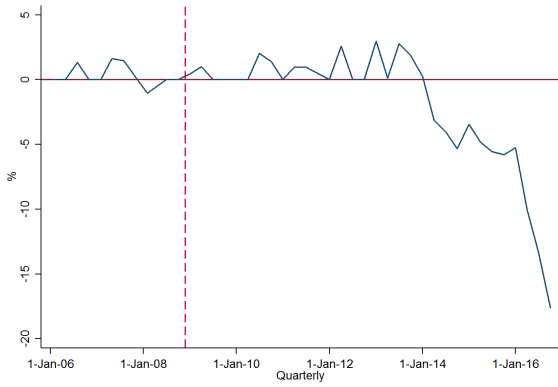
(f) Federated



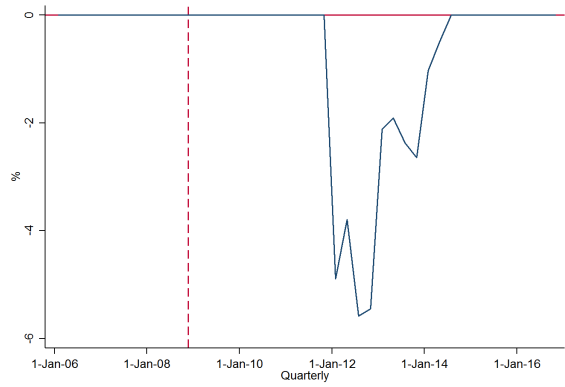
(g) MFS



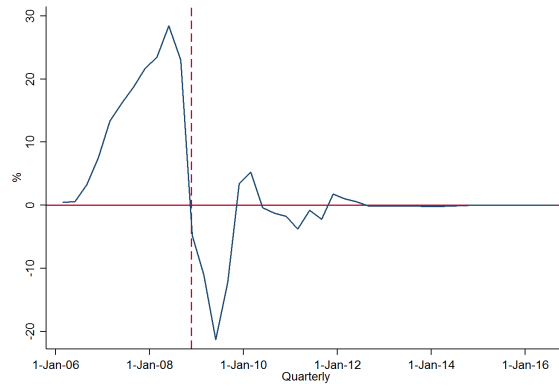
(h) Payden



(i) Goldman Sachs



(j) TCW



(k) JP Morgan

Figure 1.16: Comparison of weekly levels of average EM basis with US high yield (HY) and investment grade (IG) corporate basis is from Bai and Dufresne (2013).

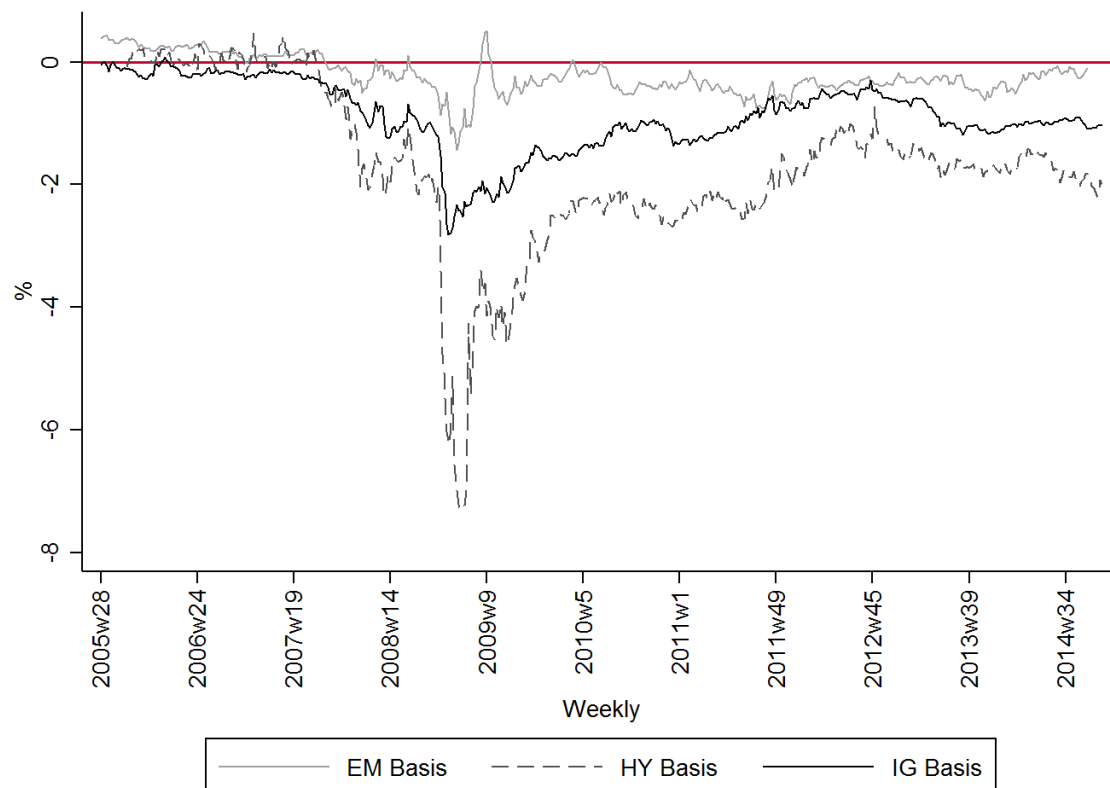


Table 1.1: Descriptive statistics for the daily sovereign yield spreads and CDS spreads in annualized percentage for remaining maturity 3 to 5 years for 23 EM. Sample period is 1/1/2004-11/14/2014.

Country	Yield Spread(3-5y)			CDS spread(3-5y)			S&P
	N	Mean(%)	Std. dev.(%)	N	Mean(%)	Std. dev.(%)	Rating
Brazil	2,736	1.7	1.16	2,735	1.84	1.32	BBB- to B+
Chile	1,341	0.6	0.55	1,315	0.55	0.61	A+ to A-
China	1,607	0.45	0.53	1,602	0.44	0.47	BBB+ to BBB
Colombia	2,699	1.81	1.04	2,696	1.68	1.09	BBB- to BB
Croatia	506	3.67	0.87	483	3.1	0.89	BBB- to BB+
Hungary	924	3.29	1.27	887	2.95	1.12	BBB to BB
Indonesia	1,432	2.28	0.91	1,201	1.76	0.77	BB+ to B
Israel	1,609	0.92	0.42	1,365	1.1	0.58	A+ to A-
Malaysia	1,005	0.4	0.23	1,002	0.29	0.17	BBB to BBB-
Mexico	2,695	1.13	0.74	2,694	1.08	0.71	BBB+ to BB
Panama	2,056	1.68	1.01	2,051	1.38	0.79	BBB to BB
Peru	1,731	1.53	0.89	1,727	1.45	0.89	BBB- to BB-
Philippines	2,668	1.91	1.1	2,451	2.1	1.29	BBB- to BB-
Poland	1,836	1.45	0.84	1,770	1.18	0.75	A- to BBB-
Qatar	1,858	1.1	0.59	1,357	0.84	0.43	AA to BBB
Russia	1,266	1.95	0.51	1,251	1.69	0.43	BBB to CC
South Korea	1,805	1.25	0.88	1,546	0.99	0.87	A+ to A-
South Africa	2,107	1.77	1.32	2,073	1.33	0.9	BBB+ to BB+
Thailand	72	0.52	0.07	72	0.29	0.05	AAA to BBB-
Turkey	2,733	2.41	1.14	2,714	2.2	0.95	BB- to B-
Ukraine	2,119	7.37	6.28	2,074	7.86	7.53	BB- to B-
Venezuela	2,048	8.72	5.09	2,046	8.95	5.97	BB- to B-
Vietnam	502	4.05	0.87	314	2.96	0.57	BB to BB-

Table 1.3: Regression of weekly change in basis on change in exogenous variables. Column (1) and (3) show results of baseline Eq(1.1) for conventional and unconventional period respectively. Column(2) and (4) show the results for baseline specification augmented with 4 lags of the exogenous variables. Newey-West standard errors with 2 lags are used. T-stats are presented in parenthesis.

$\Delta Basis_t$	
Conventional Period	Unconventional Period

		No Lag	4 Lags	No Lag	4 Lags
		(1)	(2)	(3)	(4)
$\Delta OIS\ 3m$	t	0.758*** (2.90)	0.475*** (3.75)	-0.871 (-0.85)	-0.789 (-1.09)
	t-1		-0.013 (-0.08)		1.797** (2.34)
	t-2		-0.187 (-1.53)		-0.717 (-1.01)
	t-3		-0.041 (-0.30)		1.513*** (3.29)
	t-4		-0.012 (-0.12)		-0.403 (-0.95)
$\Delta UST10y - OIS3m$	t	0.376*** (3.93)	0.445*** (7.54)	0.455*** (6.40)	0.357*** (6.98)
	t-1		-0.126** (-2.24)		-0.256*** (-5.02)
	t-2		0.040 (0.77)		-0.001 (-0.02)
	t-3		-0.140** (-1.97)		-0.102** (-2.29)
	t-4		-0.005 (-0.10)		-0.022 (-0.47)
$\Delta LIBOR3m - OIS3m$	t	-0.398*** (-5.04)	-0.510*** (-3.41)	-0.640*** (-3.53)	-0.951*** (-3.38)
	t-1		0.284** (2.09)		1.465*** (3.22)
	t-2		0.056 (0.70)		-0.578 (-1.13)
	t-3		-0.149 (-1.29)		-0.028 (-0.14)
	t-4		-0.049 (-0.61)		-0.405* (-1.69)
$\Delta OIS3m - UST3m$	t	-0.144 (-1.32)	-0.052 (-0.90)	-0.520 (-1.39)	-0.061 (-0.20)
	t-1		0.020 (0.30)		-0.673** (-2.33)
	t-2		0.002		-0.199

			(0.06)		(-0.79)
	t-3		-0.031		-0.395
			(-0.71)		(-1.38)
	t-4		0.003		-0.375*
			(0.07)		(-1.71)
ΔVIX	t	0.020**	0.007*	0.003	-0.004
		(2.05)	(1.78)	(1.01)	(-1.43)
	t-1		-0.003		-0.005**
			(-0.68)		(-2.32)
	t-2		-0.006*		-0.001
			(-1.96)		(-0.55)
	t-3		-0.009***		-0.001
			(-2.84)		(-0.26)
	t-4		0.004		0.000
			(1.38)		(0.04)
$\Delta Bank\ CDS\ 5Y$	t	0.173**	0.131***	0.147***	0.109***
		(2.38)	(2.79)	(2.88)	(2.87)
	t-1		-0.070		-0.198***
			(-1.24)		(-3.54)
	t-2		0.167*		0.006
			(1.84)		(0.17)
	t-3		0.113*		-0.152***
			(1.77)		(-3.59)
	t-4		-0.088		-0.039
			(-1.56)		(-0.84)
MSCI Return	t	-1.038***	-0.798***	-1.383***	-1.112***
		(-2.72)	(-2.67)	(-2.85)	(-2.61)
	t-1		0.813**		-0.229
			(2.52)		(-0.51)
	t-2		-0.926**		-0.120
			(-2.36)		(-0.34)
	t-3		0.277		-0.106
			(0.88)		(-0.27)
	t-4		0.619*		-0.296
			(1.96)		(-0.75)
N		253	245	306	294
adj. R^2		0.451	0.723	0.280	0.482

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

Table 1.4: Panel A shows regression result for 2-day change in basis on 2-day change in UST2y on FOMC days only. There are 41 and 50 FOMC announcements in the conventional and unconventional period respectively. Robust standard errors are used. Panel B shows the regression result for 2-day change in basis on 2-day change in UST2y for all days and dummy for the FOMC announcements (FOMC =1 on announcement days, 0 otherwise) . Newey-West standard errors with 10 lags are used. T-stats are shown in parenthesis in both panels.

Panel A		
	Δ basis (2-day)	
	Conventional Period	Unconventional Period
Δ UST2y (2-day)	0.249 (1.02)	1.425*** (3.08)
N	40	50
adj. R^2	0.023	0.431

Although conventional period has 41 announcement days, UST2y data is missing for one announcement date (1/22/2004).

Panel B		
	Δ basis (2-day)	
	Conventional Period	Unconventional Period
Δ UST2y (2-day)	0.361*** (9.06)	0.701*** (12.13)
FOMC	-0.008 (-0.45)	0.004 (0.40)
Δ UST2y x FOMC	-0.111 (-0.47)	0.724 (1.53)
N	1215	1479
adj. R^2	0.143	0.203

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.2: Compare comovement in weekly changes in yield spreads and CDS spreads in conventional and unconventional period using two metrics - a) average absolute pairwise correlation, and b) percentage variation explained by the first principal component.

	Conventional Period		Unconventional Period	
	YS changes	CDS changes	YS changes	CDS changes
Avg Correlation(%)	48.7	72.8	41.3	66.2
% Variation Explained	52.8	76.4	41.0	63.2

Analysis excludes countries with more than 50% missing observations

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

Table 1.5: Regression results of change in basis and its components, namely CDS spread and yield spread (YS), measured over 2-day and 6-day around FOMC announcements on 2-day change in UST2y. There are 41 and 50 FOMC announcements in the conventional and unconventional period respectively. Robust standard errors are used. T-stats are reported in parenthesis.

Panel A: Conventional Period

	Δ Basis(2-day)	Δ CDS(2-day)	Δ YS(2-day)	Δ Yield(2-day)	Δ Yield in GYZ
	(1)	(2)	(3)	(4)	(5)
Δ UST2y(2-day)	0.249 (1.02)	0.183 (0.53)	-0.080 (-0.58)	0.690*** (3.16)	0.977***

	Δ Basis(6-day)	Δ CDS(6-day)	Δ YS(6-day)	Δ Yield(6-day)	Δ Yield in GYZ
	(1)	(2)	(3)	(4)	(5)
Δ UST2y(2-day)	0.140 (0.70)	0.557 (1.33)	0.357 (1.15)	1.048** (2.56)	1.746***

Panel B : Unconventional Period

	Δ Basis(2-day)	Δ CDS(2-day)	Δ YS(2-day)	Δ Yield(2-day)	Δ Yield in GYZ
Δ UST2y(2-day)	1.425*** (3.08)	1.049* (1.89)	-0.450 (-1.59)	1.055*** (5.46)	1.254**

	Δ Basis(6-day)	Δ CDS(6-day)	Δ YS(6-day)	Δ Yield(6-day)	Δ Yield in GYZ
Δ UST2y(2-day)	1.060 (1.52)	1.066 (1.29)	-0.084 (-0.25)	1.612*** (5.20)	1.358

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

Column header Δ Yield in GYZ reports the OLS estimate of 2 day change in speculative grade bond yield on intraday change in UST2y in Gilchrist, Yue and Zakrajsek (2014). See text for details

Table 1.6: Regression results of 2-day change in basis on 2-day change in different proxies of US monetary policy around FOMC announcements. There are 41 and 50 FOMC announcements in the conventional and unconventional period respectively. Robust standard errors are used and T-stats are reported in parenthesis.

	Δ basis (2-day)	
	Conventional Period	Unconventional Period
Δ UST2y (2-day)	0.249 (1.02)	1.425*** (3.08)
adj. R^2	0.023	0.431
Δ OIS 3m (2-day)	-0.142 (-0.53)	0.611 (0.95)
adj. R^2	-0.007	-0.006
Δ UST3m (2-day)	-0.0961 (-0.76)	2.445*** (2.95)
adj. R^2	0.001	0.197
Δ UST10y-OIS3m (2-day)	0.205 (0.75)	0.527** (2.41)
adj. R^2	0.036	0.312
Δ UST10y-UST3m (2-day)	0.138 (0.91)	0.448** (2.08)
adj. R^2	0.036	0.233
Δ UST2y-UST3m (2-day)	0.180 (1.43)	1.305** (2.30)
adj. R^2	0.061	0.277
Δ UST10y-UST2y (2-day)	-0.0823 (-0.17)	0.433 (1.63)
adj. R^2	-0.024	0.126
N	40	50

Although conventional period has 41 announcement days, UST2y data is missing for one announcement date (1/22/2004).

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

Table 1.7: Quantitative easing related announcements from the monetary policy releases published by Fed. Highlighted rows indicate dates excluded to get a more selective indicator of QE events.

Date	News	Type	Source	Description
25-Nov-08	QE1	Expansion	FOMC Statement	Initiate a program to purchase the direct obligations up to \$100 billion in GSE debt and \$500 billion in MBS. Creation of the Term Asset-Backed Securities Loan Facility (TALF).
1-Dec-08	QE1	Expansion	Bernanke Speech	Possible purchase of long-term treasuries.
16-Dec-08	QE1	Expansion	FOMC Statement	Fed funds rate reduced to 0-0.25 range; evaluating the potential benefits of purchasing longer-term Treasury securities
28-Jan-09	QE1	Expansion	FOMC Statement	Stands ready to expand the quantity of such purchases and the duration of the purchase program as conditions warrant; also is prepared to purchase longer-term Treasury securities
18-Mar-09	QE1	Expansion	FOMC Statement	Increase the size of the Federal Reserves balance sheet further by purchasing up to an additional \$750 billion of agency mortgage-backed securities; purchase up to \$300 billion of longer-term Treasury securities over the next six months
12-Aug-09	QE1	Phase Out	FOMC Statement	Gradually slow the pace of Treasury purchase and anticipates that the full amount will be purchased by the end of October.
23-Sep-09	QE1	Phase Out	FOMC Statement	Gradually slow the pace of agency mortgage-backed securities purchases and anticipates execution by the end of the first quarter of 2010.
4-Nov-09	QE1	Phase Out	FOMC Statement	Amount of agency debt purchased will be \$175 billion instead of previously announced \$200 billion. Gradually slow the pace of its purchases of both agency debt and agency mortgage-backed securities and anticipates execution by the end of the first quarter of 2010.
10-Aug-10	QE2	Expansion	FOMC Statement	Reinvest principal payments from agency debt and agency mortgage-backed securities in longer-term Treasury securities; continue to roll over the Federal Reserve's holdings of Treasury securities as they mature
27-Aug-10	QE2	Expansion	Bernanke Speech	If necessary, expand the Federal Reserve's holdings of longer-term securities.

Continued on next page...

... table 1.7 continued

Date	News	Type	Source	Description
15-Oct-10	QE2	Expansion	Bernanke Speech	FOMC is prepared to provide additional accommodation if needed to support the economic recovery
3-Nov-10	QE2	Expansion	FOMC Statement	Purchase a further \$600 billion of longer-term Treasury securities by the end of the second quarter of 2011, a pace of about \$75 billion per month.
21-Sep-11	Operation Twist	Expansion	FOMC Statement	Maturity Extension; purchase, by the end of June 2012, \$400 billion of Treasury securities with remaining maturities of 6 years to 30 years and to sell an equal amount of Treasury securities with remaining maturities of 3 years or less.
20-Jun-12	Operation Twist Extension	Expansion	FOMC Statement	Extend maturity extension program until end of 2012
13-Sep-12	QE3	Expansion	FOMC Statement	Increase policy accommodation by purchasing additional agency mortgage-backed securities at a pace of \$40 billion per month
12-Dec-12	QE3	Expansion	FOMC Statement	Continue to purchase additional agency mortgage-backed securities at a pace of \$40 billion per month; in addition, purchase long term treasury at \$45 billion per month
22-May-13	Taper Tantrum	Phase Out	Bernanke Speech	Testify to Congress about possible taper
19-Jun-13	Taper Re- lated	Phase Out	FOMC Statement	Prepared to increase or reduce the pace of its purchases to maintain appropriate policy accommodation as the outlook for the labor market or inflation changes.
18-Dec-13	Taper Re- lated	Phase Out	FOMC Statement	Beginning in January, add agency mortgage-backed securities at a pace of \$35 billion per month rather than \$40 billion per month, and longer-term Treasury securities at a pace of \$40 billion per month rather than \$45 billion per month.

Table 1.8: Actual 1-day and 2-day change in UST2y and slope (UST10y-OIS3m) on selected QE announcements. Last column summarizes the overall change in US interest rates based on columns (1)-(4). All changes are reported as basis points.

Date	QE Selected Announcement Type	$\Delta UST2y$ (1-day) (1)	$\Delta UST2y$ (2-day) (2)	$\Delta UST10y - OIS3m$ (1-day) (3)	$\Delta UST10y - OIS3m$ (2-day) (4)	Interest Rate (5)
25-Nov-08	Expansion(QE1)	-16	-22	-17	-28	Decrease
16-Dec-08	Expansion	-10	-2	0	-20	Decrease
28-Jan-09	Expansion	2	8	12	27	Increase
18-Mar-09	Expansion	-23	-18	-50	-41	Decrease
27-Aug-10	Expansion(QE2)	5	-1	15	3	Increase
15-Oct-10	Expansion	-1	0	7	0	
3-Nov-10	Expansion	0	-1	4	-10	
21-Sep-11	Expansion(Operation Twist)	3	2	-9	-25	Decrease
20-Jun-12	Expansion	2	2	0	-2	
13-Sep-12	Expansion (QE3)	-1	2	-3	10	
12-Dec-12	Expansion	1	3	6	8	Increase
22-May-13	Phase Out (Taper Tantrum)	0	0	9	7	Increase

Table 1.9: Average change in basis on selected QE announcement days (unconventional period). The QE indicator is -1(1) if the change in UST2y is negative (positive), and is 0 on all other days. Column (1) reports β_1 in Eq (1.5) and column (2) reports β_2 in Eq (1.6). Newey-West standard errors with 10 lags are used and T-stats are reported in the parenthesis.

	$\Delta Basis(1\text{-day})$ (1)	$\Delta Basis(2\text{-day})$ (2)
QE Selected($\Delta UST2y(1\text{-day})$)	0.140* (1.95)	
QE Selected($\Delta UST2y(2\text{-day})$)		0.127** (1.98)
N	1504	1503
adj. R^2	0.033	0.017

Unconventional period - 25 Nov 2008 to 14 Nov 2014

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

Table 1.10: Average change in basis and its components on the day of the QE announcement and on the day after the announcements during the unconventional period. QE selected indicator is 1(-1) if the announcement was expansion (phase out) type and is 0 for all other days. Newey-West standard errors with 10 lags are used and T-stats are reported in parenthesis.

Panel A: Change from $t-1$ to t

	$\Delta Basis_t$	ΔCDS_t	ΔYS_t	ΔYld_t	ΔOIS_t
	(1)	(2)	(3)	(4)	(5)
QE Selected($\Delta UST2y(1-day)$)	0.140*	0.101*	-0.039**	0.063**	0.102***
	(1.95)	(1.66)	(-1.98)	(2.08)	(3.16)
N	1504	1504	1504	1504	1504
adj. R^2	0.033	0.022	0.002	0.014	0.026

Panel B: Change from t to $t+1$

	$\Delta Basis_{t+1}$	ΔCDS_{t+1}	ΔYS_{t+1}	ΔYld_{t+1}	ΔOIS_{t+1}
	(1)	(2)	(3)	(4)	(5)
QE Selected($\Delta UST2y(1-day)$)	0.004	0.071***	0.068	0.060	-0.009
	(0.12)	(3.00)	(1.43)	(1.62)	(-0.37)
N	1503	1503	1503	1503	1503
adj. R^2	-0.001	0.011	0.008	0.013	-0.000

Unconventional Period: 25 Nov 2008 - 14 Nov 2014

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

Table 1.11: Regression result of changes in net CDS sold by non-dealers on changes in US interest rates while controlling for other global variables changes (unconventional Period). For comparison, Column (4) and (5) shows the result of regressing basis changes on the same regressors. Note column (4) here is same as column (3) in Table 1.3. Newey-West standard errors with 2 lags are used. T-stats are reported in parenthesis.

		$\Delta NetSell_t$	$\Delta NetSell_t$	$\Delta NetSell_t$	$\Delta Basis_t$	$\Delta Basis_t$
		(1)	(2)	(3)	(4)	(5)
$\Delta OIS3m$	t	3.060 (0.42)	15.185** (2.06)	16.887* (1.94)	-0.871 (-0.85)	-0.109 (-0.13)
	t-1			-18.004 (-1.22)		0.966 (1.09)
$\Delta UST10y - OIS3m$	t	-1.487 (-1.25)	-2.987** (-2.16)	-3.080** (-2.27)	0.455*** (6.40)	0.409*** (7.64)
	t-1			-1.379 (-1.36)		-0.243*** (-4.52)
$\Delta LIBOR3m - OIS3m$	t		4.231** (2.30)	6.888 (1.44)	-0.640*** (-3.53)	-0.632* (-1.79)
	t-1			-1.012 (-0.14)		0.135 (0.24)
$\Delta OIS3m - UST3m$	t		-6.205 (-1.37)	-6.322 (-1.22)	-0.520 (-1.39)	-0.745* (-1.93)
	t-1			1.118 (0.19)		-0.670** (-2.46)
ΔVIX	t		-0.025 (-0.52)	-0.023 (-0.48)	0.003 (1.01)	-0.003 (-1.09)
	t-1			-0.080* (-1.67)		-0.007** (-2.23)
$\Delta Bank CDS 5Y$	t		-1.576** (-2.06)	-1.637* (-1.85)	0.147*** (2.88)	0.138*** (2.81)
	t-1			1.766** (2.31)		-0.190** (-2.39)
$MSCI Return$	t				-1.383*** (-2.85)	-1.625*** (-3.09)
	t-1					-0.246 (-0.41)
N		309	305	302	306	302
adj. R^2		0.003	0.022	0.048	0.280	0.361

Unconventional period: 25 Nov 2008 to 14 Nov 2014

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

Table 1.12: Average size and CDS position of largest mutual funds that invest in EM debt between Jan 2006 to Mar 2016. Data for monthly net flows and total net assets (TNA) is obtained from CRSP and data for quarterly CDS positions are obtained from filings by the mutual funds at SEC. Data is aggregated for all institutional share classes and reported at fund level.

Fund Group	CRSP Class Group	TNA (Mil \$)		Quarterly Average Net CDS Sold (Mil \$)		Quarterly Average Net CDS Sold/TNA (%)	
		2006m1	2016m3	Conventional Period 2006-2008	Unconventional Period 2009-2016	Conventional Period 2006-2008	Unconventional Period 2009-2016
GMO	2004084	2760	4062	1329	841	47	40
PIMCO Emerging Markets Bond	2017767	2600	1503	653	1002	23	24
Fidelity	2003386	1824	4054	0	0	0	0
PIMCO Developing Local Markets	2007584	1673	3999	7	122	0	2
SEI Institutional International	2008618	961	1464	0	0	0	0
T Rowe	2008371	519	4671	10	21	1	1
Alliance	2000821	385	6121	25	3	6	1
Fidelity Advisor	2003423	212	3301	0	0	0	0
DWS	2002324	212	119	0	0	0	0
Mainstay	2006037	189	182	0	0	0	0
Federated	2003314	188	86	-4	7	-3	7
MFS	2005905	183	3961	-1	33	-0	1
Payden	2007427	135	998	16	0	12	0
Goldman Sachs	2004297	100	1024	1	-29	0	-2
Legg Mason	2005652	92	118	0	0	0	0
TCW	2009270	71	2658	0	-42	0	-1
JPMorgan	2005407	66	905	37	-3	14	-2

Table 1.13: Regression of quarterly changes in net selling (as a % of TNA) by largest EMD mutual funds on quarterly changes in global variables. 11 of the largest mutual funds that use CDS (see Table 1.12) are included in the sample below. Fund fixed effects with clustered standard errors are used in the regression and T-stats are reported in parenthesis.

	Conventional Period		Unconventional Period	
	$\Delta NetSell/TNA$	$\Delta NetSell/TNA$	$\Delta NetSell/TNA$	$\Delta NetSell/TNA$
$\Delta OIS\ 3m$	-0.147 (-0.18)	-0.069 (-0.12)	0.596 (0.16)	2.907 (0.67)
$\Delta UST10y - OIS3m$	1.347 (0.81)	1.984 (1.04)	-1.428* (-2.12)	-1.434 (-1.66)
$\Delta LIBOR3m - OIS3m$		-5.084 (-1.20)		-0.855 (-0.45)
$\Delta OIS3m - UST3m$		2.077 (0.84)		-6.594 (-0.92)
ΔVIX		0.183 (0.95)		0.010 (0.25)
$\Delta Bank\ CDS\ 5Y$		-0.232 (-0.16)		-0.262 (-0.46)
N	107	107	251	250
adj. R^2	0.003	0.051	0.019	0.037

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

Table 1.14: Compare regression of weekly change in basis on weekly changes in global variables for US corporate debt and EM sovereign debt. The weekly data for US high yield (HY) and investment grade (IG) corporate basis is from Bai and Collin-Dufresne (2013) and the sample period is 2005w28-2014w45. Column (3) and (6) below gives the regression results of weekly EM basis shown earlier in columns (1) and (3) in Table 1.3. Newey-West standard errors with 2 lags are used and T-stats are reported in the parenthesis.

	Conventional Period			Unconventional Period		
	$\Delta HY Basis_t$ (1)	$\Delta IG Basis_t$ (2)	$\Delta EM Basis_t$ (3)	$\Delta HY Basis_t$ (4)	$\Delta IG Basis_t$ (5)	$\Delta EM Basis_t$ (6)
$\Delta OIS 3m$	0.994** (2.40)	0.312* (1.86)	0.758*** (2.90)	1.019 (0.68)	1.181*** (3.64)	-0.871 (-0.85)
$\Delta UST10y - OIS3m$	0.583 (1.40)	-0.046 (-0.42)	0.376*** (3.93)	0.485* (1.89)	-0.199*** (-3.21)	0.455*** (6.98)
$\Delta LIBOR3m - OIS3m$	-0.525* (-1.68)	-0.025 (-0.20)	-0.398*** (-5.04)	-0.973* (-1.77)	-0.217 (-1.33)	-0.640*** (-3.53)
$\Delta OIS3m - UST3m$	0.166 (1.02)	0.147 (1.39)	-0.144 (-1.32)	0.077 (0.09)	0.158 (0.55)	-0.520 (-1.39)
S&P500 Ret	4.969 (1.56)	0.027 (0.03)		1.461 (0.72)	-0.347 (-0.67)	
ΔVIX	0.009 (0.51)	-0.006 (-1.08)	0.020** (2.05)	0.014 (1.19)	-0.001 (-0.16)	0.003 (1.01)
$\Delta Bank CDS 5Y$	0.071 (0.55)	0.009 (0.19)	0.173** (2.38)	0.118 (0.95)	0.066 (1.16)	0.147*** (2.88)
$MSCI Ret_t$			-1.038*** (-2.72)			-1.383*** (-2.85)
N	162	175	253	315	315	306
adj. R^2	0.287	0.163	0.451	0.045	0.191	0.280

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

1.10 Supplementary Results

1.10.1 Data

Figure 1.17: Compare average daily yield spread constructed in this paper with average JP Morgan EMBIG yield spread. Rates are in annualized percentage.

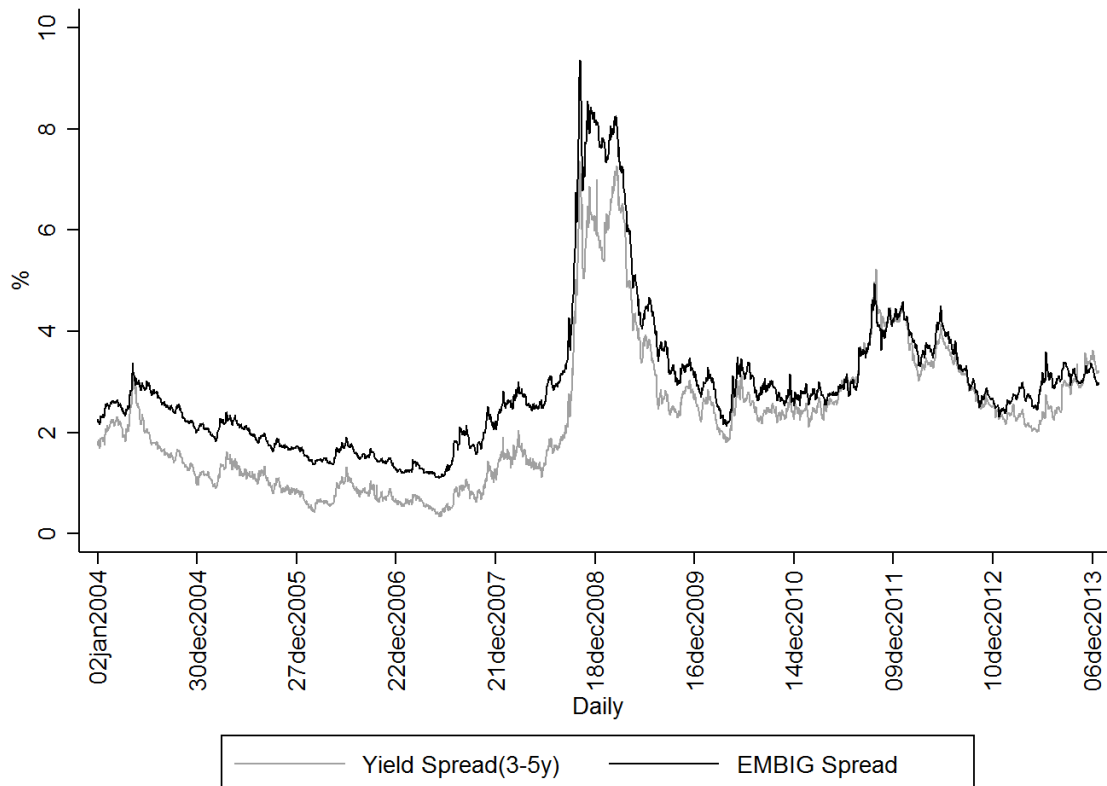
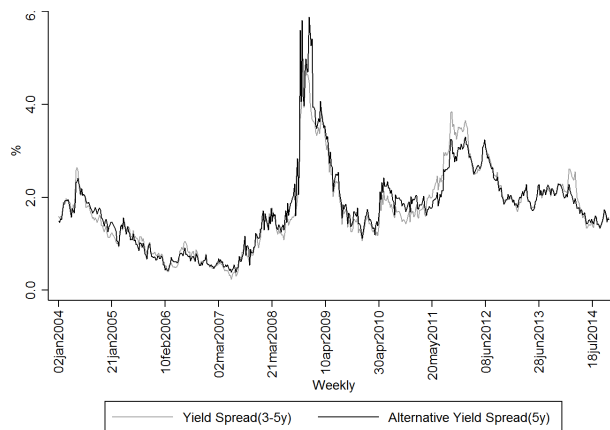
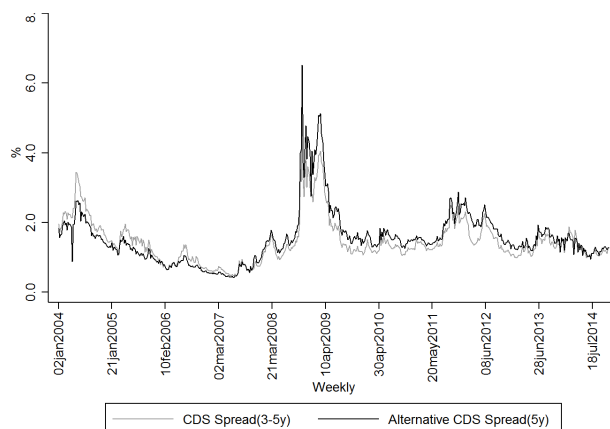


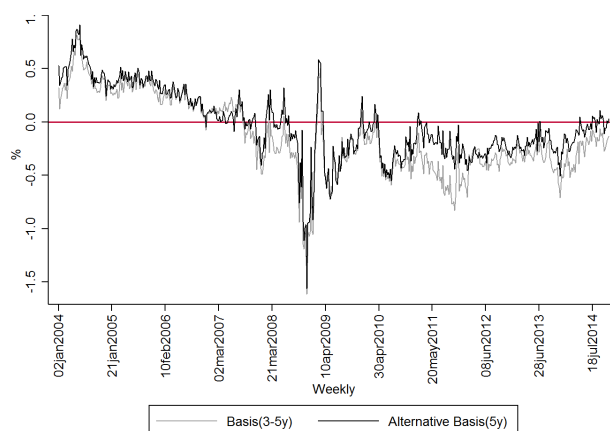
Figure 1.18: Compare weekly levels of average yield spread, CDS spread and basis constructed in this paper with alternative methodology in Fontana (2011).



(a) Compare Yield spread



(b) Compare CDS spread



(c) Compare Basis

Table 1.15: Compare regression results of changes in basis on changes in global variables between two methods - a) Basis(3-5y) is constructed by interpolating CDS spreads to match remaining maturity of bonds (my approach) b) Basis(5y) is constructed by following Fontana(2011) approach. For details see alternative basis construction methods in data section. Newey-West standard errors are used. T-stats are reported in parenthesis.

	Conventional Period		Unconventional Period	
	$\Delta Basis(5y)_t$	$\Delta Basis(3-5y)_t$	$\Delta Basis(5y)_t$	$\Delta Basis(3-5y)_t$
$\Delta OIS3m_t$	0.609*** (3.46)	0.758*** (2.90)	-0.931 (-0.88)	-0.871 (-0.85)
$\Delta UST10y - OIS3m_t$	0.375*** (6.32)	0.376*** (3.93)	0.510*** (6.86)	0.455*** (6.40)
$\Delta LIBOR3m - OIS3m_t$	-0.388*** (-4.04)	-0.398*** (-5.04)	-0.523** (-2.25)	-0.640*** (-3.53)
$\Delta OIS3m - UST3m_t$	-0.096 (-1.14)	-0.144 (-1.32)	-0.448 (-1.23)	-0.520 (-1.39)
$MSCIret_t$	-0.946*** (-3.22)	-1.038*** (-2.72)	-1.488*** (-2.94)	-1.383*** (-2.85)
ΔVIX_t	0.014** (2.26)	0.020** (2.05)	0.003 (0.82)	0.003 (1.01)
$\Delta Bank\ CDS\ 5y_t$	0.152*** (2.82)	0.173** (2.38)	0.151*** (2.95)	0.147*** (2.88)
N	253	253	306	306
adj. R^2	0.474	0.451	0.303	0.280

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

1.10.2 FOMC

To measure the effect of 2-day change in UST2y on credit spreads around FOMC announcements, I run the two following regressions for X=CDS or bond spreads. The results are shown below in Table 1.16 and 1.17.

$$\Delta_{t-1,t+1}X = \alpha_1 + \beta_1 \Delta_{t-1,t+1}UST2y + \epsilon_{1,t+1}$$

$$\Delta_{t-1,t+1}X = \alpha_2 + \beta_2 \Delta_{t-1,t+1}UST2y + \delta FOMC_t + \gamma FOMC_t \times \Delta_{t-1,t+1}UST2y + \epsilon_{t+1}$$

Table 1.16: Panel A shows regression result for 2-day change in CDS spread on 2-day change in UST2y on FOMC days only. There are 41 and 50 FOMC announcements in the conventional and unconventional period respectively. Robust standard errors are used. Panel B shows the regression result for 2-day change in CDS spread on 2-day change in UST2y for all days and dummy for the FOMC announcements (FOMC =1 on announcement days, 0 otherwise) . Newey-West standard errors with 10 lags are used. T-stats are shown in parenthesis in both panels.

Panel A		
	Δ CDS (2-day)	
	Conventional Period	Unconventional Period
Δ UST2y (2-day)	0.183 (0.53)	1.049* (1.89)
N	40	50
adj. R^2	-0.017	0.145

Although conventional period has 41 announcement days, UST2y data is missing for one announcement date (1/22/2004).

Panel B		
	Δ CDS (2-day)	
	Conventional Period	Unconventional Period
Δ UST2y (2-day)	-0.262*** (-2.97)	-0.304*** (-3.75)
FOMC	-0.016 (-0.55)	0.001 (0.04)
Δ UST2y x FOMC	0.445 (1.25)	1.353** (2.56)
N	1215	1479
adj. R^2	0.031	0.049

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

FOMC =1 on announcement days, 0 otherwise

Table 1.17: Panel A shows regression result for 2-day change in yield spread on 2-day change in UST2y on FOMC days only. There are 41 and 50 FOMC announcements in the conventional and unconventional period respectively. Robust standard errors are used. Panel B shows the regression result for 2-day change in yield spread on 2-day change in UST2y for all days and dummy for the FOMC announcements (FOMC =1 on announcement days, 0 otherwise) . Newey-West standard errors with 10 lags are used. T-stats are shown in parenthesis in both panels.

Panel A		
	Conventional Period	Unconventional Period
Δ UST2y	-0.080 (-0.58)	-0.450 (-1.59)
N	40	50
adj. R^2	-0.018	0.048

Although conventional period has 41 announcement days, UST2y data is missing for one announcement date (1/22/2004).

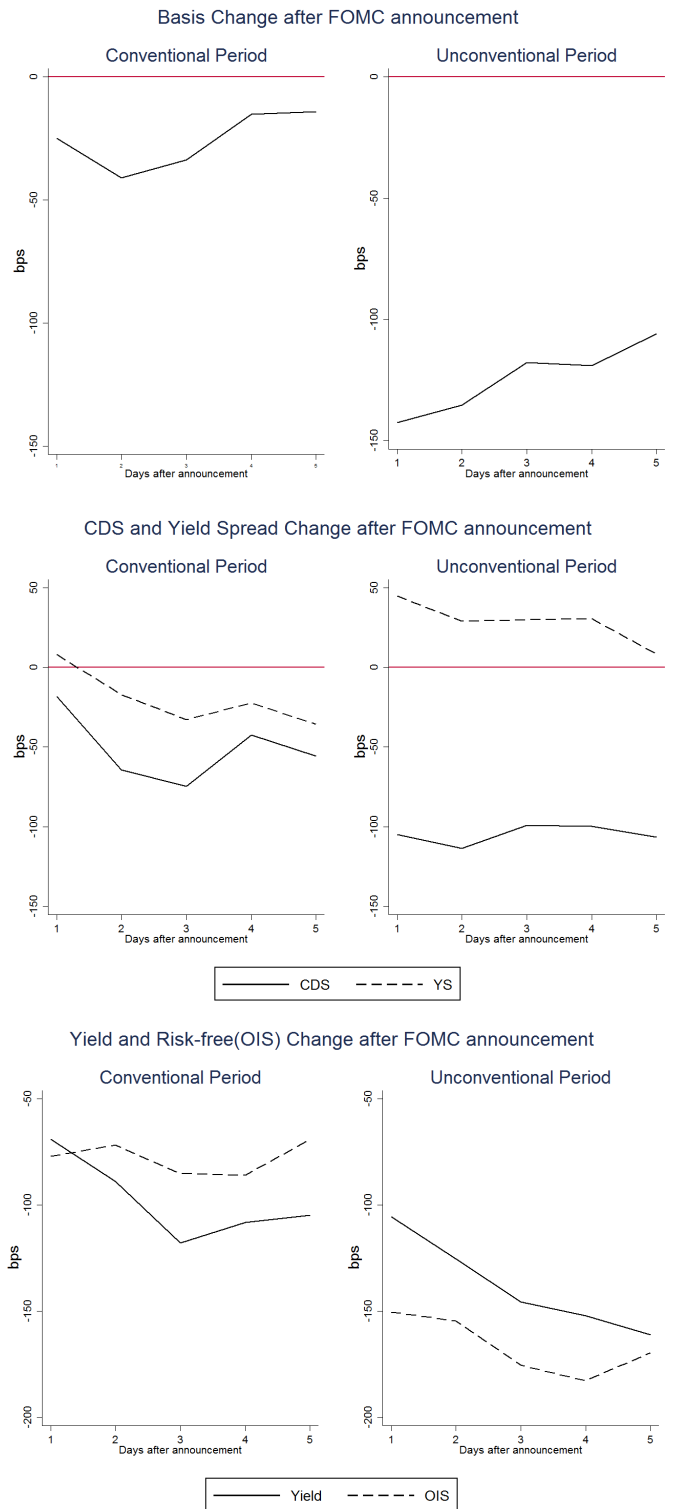
Panel B		
	Conventional Period	Unconventional Period
Δ UST2y	-0.618*** (-10.42)	-1.009*** (-13.08)
FOMC	-0.007 (-0.47)	-0.006 (-0.51)
Δ UST2y x FOMC	0.538*** (3.58)	0.559** (2.45)
N	1215	1479
adj. R^2	0.270	0.298

Conventional - 1 Jan 2004 to 24 Nov 2008; Unconventional - 25 Nov 2008 to 14 Nov 2014

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

FOMC =1 on announcement days, 0 otherwise

Figure 1.19: Change in basis and its components 1,2,...,5 days after FOMC announcements in response to -100 bps 2-day change in UST2y.



1.10.3 DTCC

Figure 1.20: Comparison of the gross size of the market for single-name CDS and CDS indices. The top figure shows the size of only the sovereign CDS and the bottom figure shows the same for all CDS combined.

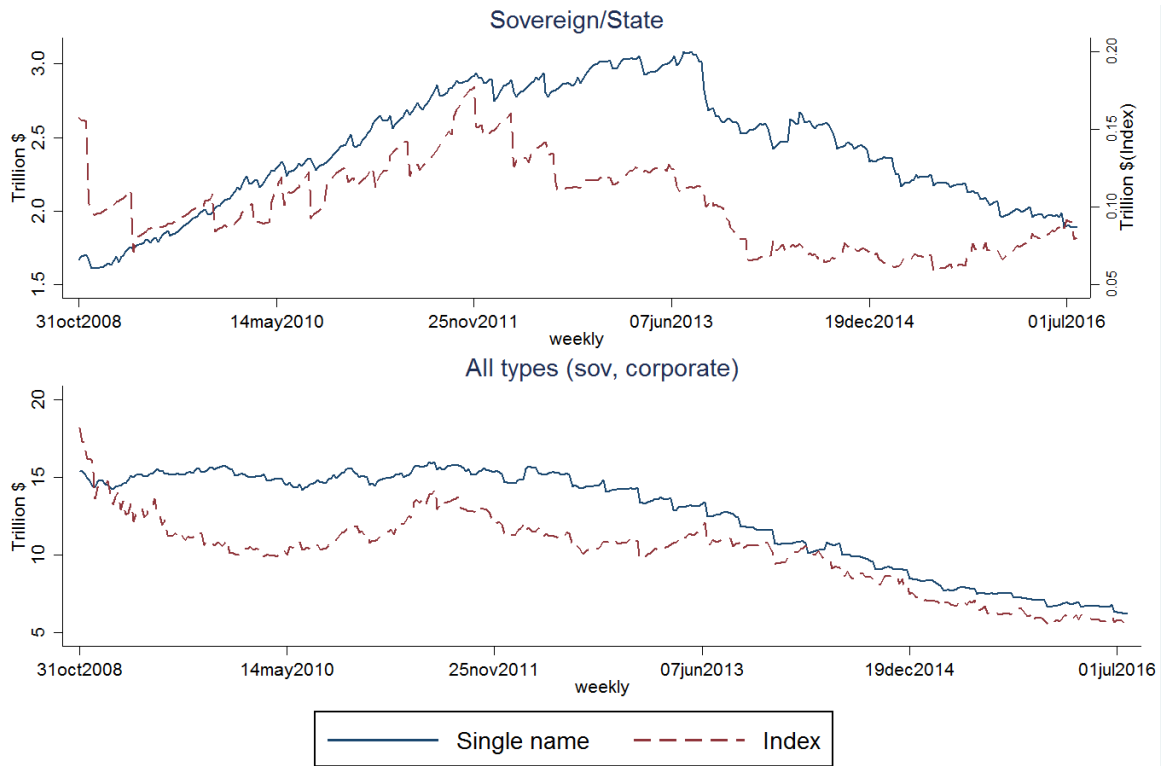
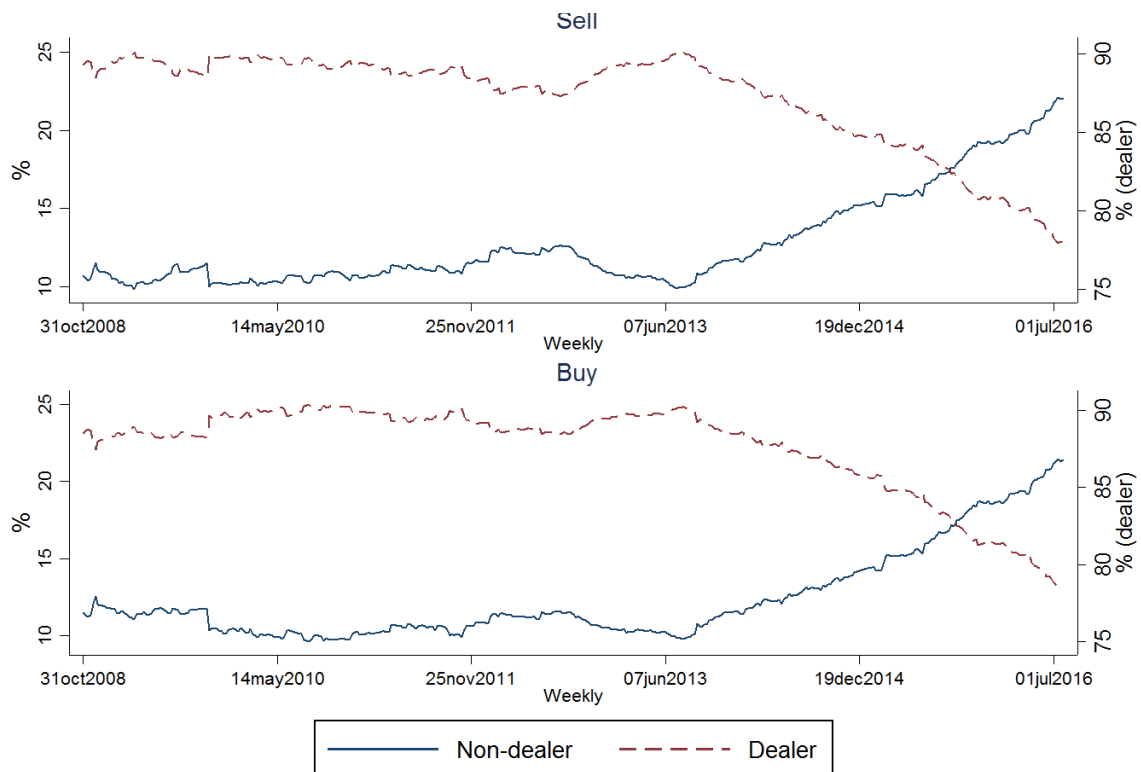
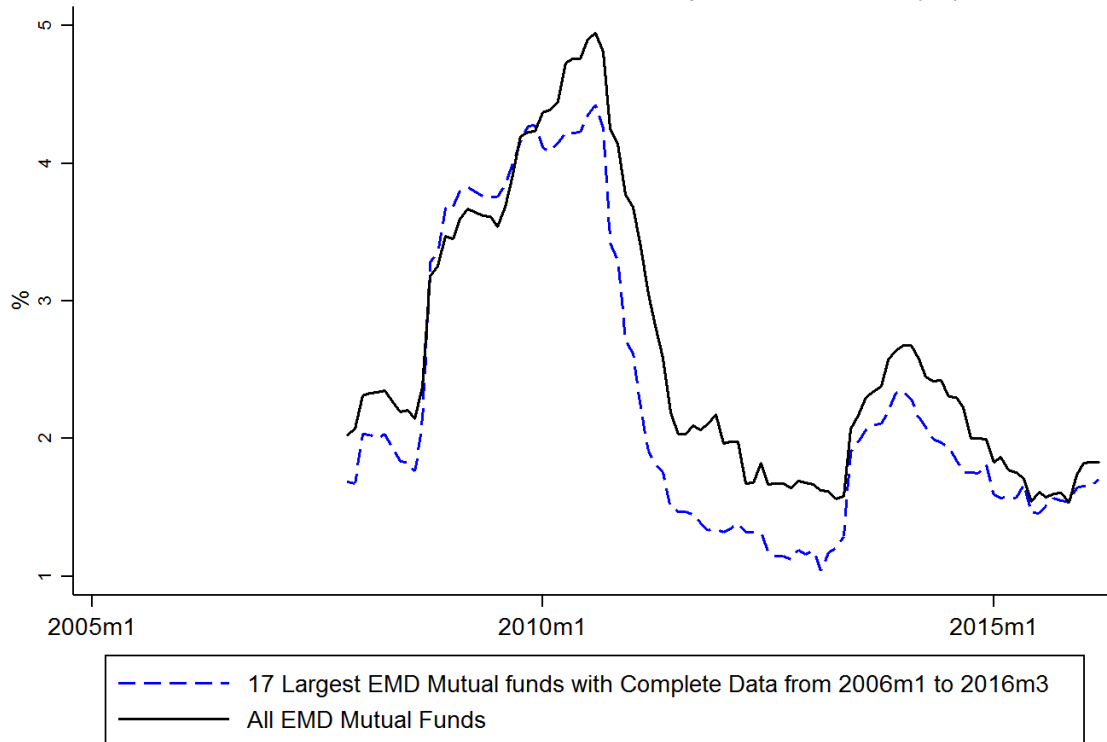


Figure 1.21: Percentage of total gross notional sovereign CDS bought and sold by investor type. The top figure compares % sold by dealers and non-dealers and bottom figure compares the % bought by them.



1.10.4 Mutual Funds in EM CDS market

Figure 1.22: Compare rolling standard deviation (over 24 months) of aggregate net flow/ net assets of all mutual funds who invest in EM debt and 17 largest (as of 2006m1) EMD mutual funds from 2006m1 to 2016m3.



CHAPTER II

A System-wide Approach to Measure Connectivity in the Financial Sector

2.1 Introduction

There has been a growing interest in understanding and measuring *systemic risk*, largely driven by the events of the 2007-09 financial crisis. A number of such measures have been proposed, including conditional Value-at-Risk (CoVaR) (*Adrian and Brunnermeier (2011)*), CoRisk (*Chan-Lau et al. (2009)*), systemic expected shortfall (SES) (*Acharya et al. (2012)*) and, SRISK (*Brownlees and Engle (2015)*), to name a few. Another strand of literature proposes network connectivity of large financial institutions as a way to identify systemically important institutions based on the centrality of their role in an appropriately constructed network, e.g., network of the corresponding firms' stock returns (see *Billio et al. (2012b)*).

There is broad agreement that systemic risk threatens the stability of the entire financial system and hence any associated risk measures should provide a systemwide perspective. However, there is relatively little theoretical guidance on how to measure systemic risk; therefore, understanding the econometric properties of the proposed

measures of this risk becomes even more important.¹

Since systemic risk represents a property of the entire financial system, interconnectedness of the participants represents a key element. For example, highly interconnected institutions that are likely to fail pose a higher risk to the system due to the presence of multiple channels of transmission and contagion. Hence, at their core all proposed measures of systemic risk aim to reflect connectivity. For example, SES and CoVaR assess the association between a given financial institution's condition with that of the rest of the financial system and more broadly the economy. The larger the magnitude of these associations, the higher is the systemic risk of a given institution. Network based approaches directly aim to measure connectivity between financial institutions and subsequently derive summary network measures as proxies for systemic risk. However, extant measures of systemic risk often fall short of a true system-wide measure of connectivity. Our paper highlights this limitation of the current literature, and then proposes a solution.

We primarily focus on a network based approach akin to that adopted in *Billio et al.* (2012b) to illustrate our key point. *Billio et al.* (2012b) estimates a bivariate Granger causal association on the stock returns of large financial firms of the economy where firm A is said to be connected to firm B if A Granger-causes B , i.e., return of firm A at time t has additional predictive power in forecasting return of firm B at $t+1$, over and above the lagged returns of firm B . While this is a useful starting point, such pairwise approach of learning network structures misses out on the system-wide

¹Earlier theoretical work has mainly focused on banking and currency crises. These models provide extremely valuable insights into the microeconomic foundations of crisis, but they do not take us all the way to a measure of systemic risk that can be implemented in practice, e.g., see *Allen and Gale* (1998) and *Diamond and Dybvig* (1983) for some early contributions. Papers by *Battiston et al.* (2012), *Acemoglu et al.* (2015) and others have made considerable progress in the literature in recent years. These papers provide valuable insights into the shape of network structure, the mechanism of the shock propagation, and the resulting implications for the fragility of the system.

connections. Specifically, a pairwise measure of statistical association between any two firms A and B gives the direct strength of connectivity between A and B , as well as indirect effects through all the other nodes in the network. As a result, a network based on such marginal effects of A on B does not pin down institutions that are key in propagating the risk in the system. We illustrate this issue in Figure 2.1. The figure plots the true network structure for a three firm system. In this hypothetical system, there are 3 causal effects in the model: $B \rightarrow C$, $B \rightarrow A$, $C \rightarrow B$. However, due to indirect effect through B , there is additional (spurious) pairwise Granger causal effect $C \rightarrow A$. Measures such as SES and CoVaR partially mitigate this issue by considering statistical relationships between an institution and the system as a whole. However, even with these measures a similar concern arises since these models estimate the covariance of an institution with the rest of the system without conditioning it on all other participants. While our focus is on pairwise Granger causal network, we explore this issue for other measures further in Section 2.4 of the paper.

The key issue in the above example is that the pairwise metric does not take into consideration the effects of the third institution on the pair under consideration. Conceptually, the misspecification problem of the pairwise Granger causal effect is analogous to the well understood omitted variable bias in standard regression models. Statistically, the model parameters end up being inconsistently estimated, which in turn may lead to large economic costs; for example, a number of institutions that are not highly interconnected may end up being wrongly classified as interconnected under such an approach. Hence policy designs, such as linking a bank's capital requirement based on their interconnectedness in the network, are likely to be problematic with such a structure. Similarly, such an approach may not be meaningful in identifying systemically important firms of the financial system.

One approach to correctly identify the interconnectedness structure of the system is to fit a VAR model that takes into consideration *all* interactions amongst the system’s components. This can be done, for example, by estimating the VAR model with all firms simultaneously, instead of a pair-wise approach. However, the number of parameters to be estimated even for the simplest lag-1 VAR model in this approach is quadratic in the number of institutions under consideration. For example, to estimate a full VAR(1) model for 100 financial institutions, we need over 10,000 time periods for estimation. In most practical applications, this seems infeasible. We suggest a statistical approach based on recent developments in higher dimensional statistics that overcomes this challenge.

We employ a regularized VAR model, using LASSO (Least Absolute Shrinkage and Selection Operator) techniques, that only focuses on estimating the *strongest* interconnections, while forcing weaker relationships to zero. The key statistical advantage of this approach is that we need significantly lower number of time points to estimate this model as compared to the classical estimation of the VAR model as long as the underlying network is approximately sparse. We provide an in-depth discussion of our statistical approach in Section 2.3 with additional technical details in the Supplementary Discussion. The method provides statistically consistent estimates of the network’s interconnectedness, which constitutes the first step towards gaining insights about interconnectedness patterns during periods of financial calmness and juxtapose them to those during financial distress. As *Glasserman and Young* (2015) argue, the role of growing interconnectedness of the financial system is one of its least understood aspects.

Among the extant approaches to measure systemic risk, perhaps the closest to a system-wide approach is the one developed in *Diebold and Yilmaz* (2014). In this work,

the authors fit vector autoregressive (VAR) models simultaneously for all firms and use variance decomposition of the forecast error of the fitted model to define the network topology and extract connectivity measures. Since *Diebold and Yilmaz* (2014) estimate a full VAR model, a limitation of their approach is that their model can be estimated only for a limited number of firms (e.g., 15 firms in their study) since the estimation of a full VAR model requires extremely large amount of data. Our model, on the other hand, can be useful for a more realistic setting involving all important banks of the economy.

After discussing the statistical underpinnings of our model, we conduct some simulation exercises to highlight the advantages of our measure over the existing ones. In our first simulation exercise, we simulate data on lead-lag relationship between financial institutions based on lag-1 VAR model. On the simulated data, we estimate connections based on both our model (which we refer to as Network Granger Causal model) and the bi-variate VAR model. Our model does considerably better in detecting the true network structure. We also compute CoVaR and MES measures on this simulated data and show the improvement our model achieves.

The use of a first-order VAR model of stock returns may not be an innocuous assumption. In efficient markets, past stock returns of other financial institutions should not have any predictive power for explaining the return of any other institutions. Market inefficiency, slow diffusion of information and frictions such as short-selling restrictions can be a potential reasons for non-trivial dependence between the returns of different institutions over time. However, our paper does not rely on this specific form of interdependence across the institutions' returns. Using the idea of partial correlations, a system-wide approach can be taken to capture contemporaneous connectivity as well. Building on this idea, we next simulate a model that only has contemporaneous

correlations across institutions' returns and contrast our approach with other models such as CoVaR and MES. Again, our model performs better in capturing the true connections. Given the very infrequent occurrence of actual systemic events that can be used to evaluate the relative performance of different models, our simulation exercise is especially important in establishing the usefulness of our approach.

In the final part of the paper, we estimate our model using the stock return data of three important sectors of the financial services industry, namely banks, broker-dealers and insurance companies. The financial institutions in these sectors are intricately related through both direct business relationships such as lending and borrowing, and through indirect relationship such as “spillover effects” through correlated trading or exposure to common assets.² Theoretical works such as *Allen and Gale* (2000), *Babus* (2013), *Acemoglu et al.* (2015) discuss direct linkage formation among firms through lending. On the other hand, some recent papers focus on connectedness via trading activities of firms. *Colla and Mele* (2010) discusses information network among investors while *Brunnermeier and Pedersen* (2009b) shows how funding of traders with capital constraints and risk limits are affected by destabilizing nature of margin-based trading. In this paper, we are agnostic about the reasons behind connections in the first place. Rather, our focus is on the measurement of the resulting interconnectedness.

Using our LASSO penalized lag-1 VAR model, we estimate the network structure over time, on a rolling basis, from year 1992 to 2012. We show that different measures of connectedness based on the number of firms connected to each other (degree) and the shortest path length from one firm to another in the network (closeness), exhibit sharp peaks just before important systemic events such as the dot-com related market crash in 2000 and the Lehman Brothers' failure in 2008.³ Thus our network is useful in

²*Billio et al.* (2012b) discusses increased financial linkages across these types of institutions.

³There are several possible measures of centrality in networks such as degree, closeness, betweenness

providing information on the buildup of systemic risk in the financial system. Needless to say, with limited number of systemic events in the economy, we are unable to carry out any formal statistical test for the predictive power of our network. However, it is clear that our results line up well with identifiable periods of systemic risk in the economy.

Our network estimates allow us to detect institutions that are relatively more important in the network at any given point in time. Higher the degree of a firm, larger is the number of its immediate neighbors. Higher closeness, on the other hand, indicates how easily the firms can be accessed by other firms in the network. We find that AIG becomes one of the most important nodes in our network before and during the recent financial crisis. This finding is consistent with anecdotal evidence that highlights the central role of AIG in the economy during the 2007-2009 period. We provide the ranking of institutions at different points in time during our sample period, and these rankings can be useful inputs to policy decisions on the detection of systemically important institutions. Based on our estimates we find that banks that were closely linked to AIG experienced larger negative returns in the immediate aftermath of the failure of Lehman, providing confidence in our estimation method.

Our network estimate picks up strong relationships, which are likely to be more meaningful for policy decisions. We contrast our estimated network with that in *Billio et al.* (2012b) which is significantly more dense. Said differently, in their pairwise network, institutions on average are connected to several others since the estimation does not parse out indirect relationships between institutions. Thus the *pairwise* Granger causal approach ends up with too many connections between institutions as

and eigenvector. Without a clear theoretical guidance, it is unclear which measure is most suited for systemic risk applications. Hence we present our results for two most widely used measures used often in studies of network model.

opposed to our *network* Granger causal approach.

In summary, our paper contributes to the literature by estimating the network structure in a statistically principled way, specifically a measure of network that is consistent and mitigates, to a large extent, the omitted variable bias inherent in pairwise methods. Since any error in the misclassification of systemically important institution can be very costly for the economy, our paper provides a considerable improvement in designing and implementing efficient macro-prudential regulations. Our approach can be useful in a number of different settings where researchers are likely to be interested in both direct and indirect linkages between several firms in a network. For example, our methodology can be useful in detecting supplier-customer stock return relationships for a large number of firms. Similarly, our method can be helpful in estimating the effect of common owners or board members on firm policies. Our paper provides self-contained guidance on estimating a true Network Granger Causal model for applied researchers in different areas of finance and economics.

Section 2.2 expands on the biases created by pairwise approach and highlight the limitations of extant measures of systemic risk. Section 2.3 proposes our Lasso penalized VAR measure. In Section 2.4, we show the usefulness of our measure, compared to existing measures, on simulated data sets. Section 2.5 presents the estimation result with actual data for 75 largest financial institutions of the U.S. Section 2.6 concludes.

2.2 Pair-wise versus system-wide approaches

We elaborate on the problem statement and potential biases created by extant measures in this section. Throughout this paper, we use $A_{i\cdot}$ and $A_{\cdot j}$ to denote the i^{th} row and j^{th} column of a matrix A , respectively. We also use the standard notations

for norms of a p -dimensional vector $\|v\|_\infty = \max_{j=1,\dots,p} |v_j|$, $\|v\|_1 = \sum_{j=1}^p |v_j|$. For a $m \times n$ matrix A , we denote its Frobenius norm as $\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n A_{ij}^2}$.

Consider a network of 15 institutions with 5 hubs, each with one central firm. In each hub, the middle firm is central and propagates shocks to other firms. Firms on the periphery, on the other hand, do not propagate any shocks to other firms (see Figure 2.2). Such a dynamics can be modeled by assuming a data generating process in which the middle firm's return in period t affects the returns of both firms on the periphery in period $t + 1$. We capture this idea by simulating data as per the dynamics below:

$$\begin{aligned} R_2^{t+1} &= 0.6 * R_2^t + \epsilon_2^{t+1} \\ R_j^{t+1} &= 0.6 * R_j^t + 0.4 * R_2^t + \epsilon_j^{t+1}, \quad j = 1, 3 \\ \epsilon_j^t &\stackrel{i.i.d.}{\sim} N(0, 1) \end{aligned}$$

We simulate this model with 500 independent draws. Based on the simulated data, we fit a pair-wise VAR model in line with *Billio et al. (2012b)*. For each pair of firms, we estimate the lead-lag relationship between their returns using an OLS model. It is worth emphasizing that in this approach each estimation exercise ignores the effect of all other firm' returns on the returns of the pair under consideration.

The true network as well as the estimated pairwise Granger causal network are depicted in Figure 2.2. The estimated network structure detects significant relationships between the adjacent peripheral firms in each hub in addition to the relationship between the central firm and the rest. Thus, the estimated network structure provides an incorrect picture of the true network. The reason is simple. The pairwise model ignores the fact that returns of both peripheral-firms are driven solely by the central firm. Ignoring the effect of the central firm's returns while estimating correlations be-

tween the returns of firms on the periphery, leads to false positives connections. In other words, the pairwise model ignores the conditional independence in returns of firms on the edges, conditional on the central firm's returns.

After estimating the network structure, researchers often use statistics such as the degree of a node (i.e., number of important connections a particular node has) as a measure of the importance of the node in the network. In the above example, the pairwise model estimates a degree of 2 for both the adjacent nodes, as compared to its true degree of 1. Thus, the use of this network structure can lead to misleading inferences. An immediate solution to this problem is to estimate the VAR model simultaneously with all firms in the system. However, such an approach is not feasible with standard techniques due to data limitations. For example, if we have 100 large institutions in the system, then a VAR(1) model needs to estimate 10,000 (100×100) parameters! This is often impossible due to relatively fewer samples and regime changes in the underlying system. Our proposed method overcomes this problem of dimensionality and allows us to estimate the model structure in a very wide range of situations.

While it is relatively straightforward to see the difference between a pair-wise and a system-wide approach in the case of VAR model discussed above, even other models such as MES and CoVaR face this challenge. For example, consider CoVaR. It measures the value-at-risk of the entire financial system conditional on the value-at-risk of a given institution. For firm i value-at-risk at a confidence level q represents the extent of losses that will not be exceeded with a probability greater than q . CoVaR measures the probability that the entire system is in distress (i.e., the return of the entire system is below some threshold) conditional of bank i hitting its VaR limit. A related measure, $\Delta CoVaR$ measures the difference in CoVaR when the firm i is in its median state

compared to the same firm being in a distressful state. More formally:

$$\begin{aligned}\mathbb{P}(R^i \leq VaR_q^i) &= q \\ \mathbb{P}(R^{system} \leq CoVaR_q^{system|R^i=VaR_q^i} \mid R^i = VaR_q^i) &= q \\ \Delta CoVaR_q^{system|i} &= CoVaR_q^{system|R^i=VaR_q^i} - CoVaR_q^{system|R^i=VaR_{50\%}^i}\end{aligned}$$

As can be seen from the above discussion, CoVaR only conditions on the distress of one financial institution at a time. Thus it misses out the effect of all other firm's returns on the system, and just like pairwise VaR it attributes all the indirect linkages as a direct linkage between firm i and the system. For example, assume that JP Morgan Chase is the most vital bank in the system in the sense that its distress leads to distress of the entire system as well as a specific bank, Citi Bank. Even if Citi Bank, in our example, is systemically unimportant, CoVaR is likely to pick it up as an important systemic bank. The underlying issue is the same: CoVaR of Citi Bank does not consider the indirect effect of JP Morgan Chase.

MES, defined as the expected return of firm i when the system is at its lower tail, provides some improvement by conditioning on the system as a whole. However, it still computes a pairwise measure. Formally, MES is defined as follows (we take negative of the expected return so that the measure increases in systemic risk:

$$MES = -E(R^i \mid R^{system} \leq R_q^{system})$$

If firm j is the central node that affects both firm i and the system as a whole, then we will find a significant relationship between firm i 's returns and the system as a whole in a model that excludes firm j from it.

Ideally, we want to compute the CoVaR and MES measures of an institution after conditioning on the effect of *all* other firms in the system. For example, the notions of CoVaR and MES can be generalized in a system-wide fashion by including the omitted firms in the conditioning set as follows:

$$\mathbb{P}\left(R^{system} \leq CoVaR^{system|R_q^i} \mid R^i = VaR_q^i, R^j = VaR_{50\%}^j, R^k = VaR_{50\%}^k, \dots\right) = q$$

However, estimation of such measures will face similar statistical challenges due to over-parameterization, which will require additional econometric considerations. For expositional simplicity, we first discuss our modified VAR model and later return to a discussion of these other measures of systemic risk.

2.3 Model and Method Description

To overcome the limitations presented above, we adopt an approach that has both sound statistical and economic properties. At a very broad level, our statistical approach forces weak relationships among institutions in the network to zero, allowing us to take a true system-wide approach in estimating the model with limited data. In economic terms, this approach is both sensible and useful for policy designs. As we discuss in detail later in the paper, numerous studies have shown that financial institutions form trading or counter-party relationships with only a handful of other institutions. Hence, the assumption of sparsity that underlies our estimation is reasonable in our context. Second, when regulator have limited resources, it is advantageous to focus on stronger connections in the network. Our model allows us to do this.

We estimate the network connectivity among p institutions based on a p -dimensional VAR(1) model of stock returns (after suitable transformation to reduce nonstationar-

ity). The transition matrix of this model reflects strengths of lead-lag relationships between returns of two institutions, *conditional* on the returns of all the other ones in the sample. To ensure consistent estimation of our model with limited sample size ($n \ll p$), we assume *sparsity* of the true underlying financial network, and motivate this assumption by pointing to empirical evidence in section 2.3.1. The posited sparsity assumption implies that a large number of elements in the transition matrix are zero, and hence fewer parameters need to be estimated from the available data.

As we describe in section 2.3.2, such a sparse VAR model can be consistently estimated using a penalized (Lasso) regression framework with small sample size. However, using the sparse Lasso VAR estimates directly to assess network connectivity faces two issues - (i) this estimate does not come with associated uncertainty measures (e.g. confidence intervals), and (ii) sparsity of the network relies on a non-obvious choice of a tuning parameter. Our proposed debiased Lasso VAR estimates mitigate both issues by allowing us to formally test for Granger causality, and form a network with statistically significant relationships as edges. The problem of selecting the critical tuning parameter then reduces to the familiar specification of significance level in hypothesis testing. By varying the level of significance (e.g., 1%, 5%, 10%), we can change the levels of sparsity in our estimated networks. Given that we carry out *simultaneously* p^2 tests (one for each debiased edge in the network), we need to correct for the well known multiple comparisons problem. After doing so, the resulting significant edges are used to construct the Granger causal network of interest, which is summarized by using various standard network measures such as degree and closeness to detect highly connected and thus systemically important institutions.

2.3.1 VAR models and network Granger causality

We model the process of stock returns of p firms $X^t = (X_1^t, \dots, X_p^t)'$ using a p -dimensional Gaussian VAR(1) model.⁴⁵

$$X^t = AX^{t-1} + \varepsilon^t, \quad \varepsilon^t \sim N(0, \Sigma_\varepsilon), \quad \Sigma_\varepsilon = \text{diag}(\sigma_1^2, \dots, \sigma_p^2) \quad (2.1)$$

In this model, the $p \times p$ transition matrix A can be viewed as a weighted, directed network $G = (V, E)$ amongst financial institutions, with the set of nodes $V = \{1, 2, \dots, p\}$ and the set of edges $E = \{(i, j) : A_{ij} \neq 0\}$. The weight of an edge (i, j) , denoted by $|A_{ij}|$ measures the strength of connections. For ease of presentation, we work with the undirected, unweighted *skeleton* of the network G , denoted by $\mathcal{S}(G)$, where there is an edge $i - j$ between institutions i and j if $\max\{|A_{ij}|, |A_{ji}|\} \neq 0$.

The VAR model allows one to generalize pairwise Granger causality towards Granger's original definition of causality (*Granger*, 1969, 1980). A series X_1 Granger-causes another series X_2 if

$$\sigma^2(X_2^{t+1} | \mathcal{I}(t)) < \sigma^2(X_2^t | \mathcal{I}(t) - \mathcal{I}_{X_1}(t)),$$

where $\sigma^2(A|B)$ denotes the variance of the prediction error, when predicting A using the best linear predictor constructed from information set B , and $\mathcal{I}(t)$ captures *all available information in the universe* up to time t . For pairwise Granger causality analysis, the information set $\mathcal{I}(t)$ is restricted to the information in the two series X_1 and X_2 up to time t . A joint VAR model allows one to expand the set $\mathcal{I}(t)$ to

⁴We chose the VAR order to be 1 for ease of exposition. Networks can be estimated by combining information of transition matrices from different lags in a VAR(d) models (*Basu et al.*, 2015).

⁵In the data analysis, we use residuals of a GARCH model fitted to the univariate series of returns. Other suitable transformations can be applied to adjust for non-Gaussian heteroskedasticity in data. Our statistical methodology is general and can be applied on other characteristics of the institutions; e.g., volatilities (after log transformation), leverage ratios etc.

include information contained in *all* p series X_1, X_2, \dots, X_p . Conditioning on this larger information set is the *central theme* of our system-wide approach, as we also emphasize in section 2.4 in the context of contemporaneous dependence. To emphasize its importance in constructing the network representation of the system, we refer to this notion as *network Granger causality* (Basu et al., 2015). The entries of the VAR transition matrix A capture the network of Granger causal relationships with respect to this larger information set.

The choice of the information set $\mathcal{I}(t)$ is an important consideration in multivariate Granger causality analysis, well-known in the time series and econometrics literature. Failure to include relevant information outside the two series under investigation often results in a spurious Granger causal relationship among the observed series, which essentially captures indirect effects coming via the unobserved omitted variables. Another view of using VAR models to estimate network connectivity among stock returns of p financial institutions is also related to the general theory of graphical models popular in statistics and machine learning (Wainwright and Jordan, 2008), since the transition matrix A of a Gaussian VAR(1) model with diagonal Σ_ε determines the adjacency matrix of the Directed Acyclic Graph (DAG) which characterizes the conditional independence relationships among firm characteristics in their joint distribution (Eichler, 2012).

Sparsity of Financial Networks. We assume the network is *sparse*, i.e., the number of edges present in the network ($s := \|A\|_0 = \sum_{i,j=1}^p \mathbb{1}[A_{ij} \neq 0]$) is very small compared to the total number of possible edges p^2 . For example, in a network with 100 institutions, we have 10,000 parameters in a first-order VAR model. We require the true number of interconnections in a 100 institution network to be much smaller than 10,000. This is a reasonable assumption for our application. First, each financial insti-

tution is unlikely to form strong relationships with all others in the sample simply due to the costs involved in starting and maintaining such relationships. This is especially true in information-sensitive markets involving non-trivial search costs (e.g., see discussion in *Gofman* (2016)), where institutions often rely on repeat transactions with a relatively smaller set of institutions. Empirical evidence from inter-bank relationships provide strong support for this assertion. For example, *Soramäki et al.* (2007) analyze daily networks in the first quarter of 2004 using interbank payments transferred between commercial banks over the Fedwire. Based on actual data they find few highly connected banks and the great majority of banks having few counterparties. That the degree distribution (number of counterparties for each bank) roughly follows the power law distribution with few core banks and several small banks is reported for several interbank market across the world (e.g *Bech and Atalay* (2010), *Boss et al.* (2004), *Iori et al.* (2008), *Craig and Von Peter* (2014), *Blasques et al.* (2015)). If the underlying network structure is not very sparse but has a few strong and many weak relationships, our model will be able to detect strong relationships forcing the weaker ones to zero (*Bühlmann and van de Geer*, 2015; *van de Geer and Stucky*, 2016). Again, from an economic viewpoint this is a reasonable property of our model since we are mainly interested in strong connectivity relationships to begin with.

In the next section, we provide a short overview of the existing machinery for estimating large VAR models and describe our method, which builds upon a bias-corrected Lasso procedure originally proposed in *Javanmard and Montanari* (2014) and extended in this paper for time dependent data.

2.3.2 Estimating large VAR models

Historically, the most common method for estimating the transition matrix A is on an equation-by-equation basis, by ordinary least squares (OLS) regression of X_i^t on $X_1^{t-1}, X_2^{t-1}, \dots, X_p^{t-1}$, for $i = 1, \dots, p$. However, the OLS estimate is ill-defined when the number of predictors is larger than the number of observations i.e, $p > n$. A VAR(1) model with p variables requires estimation of p^2 free parameters, which in turn requires at least $O(p^2)$ samples for meaningful estimation. Therefore, without imposing any additional restrictions on the parameters, it is not possible to estimate such a VAR model.

Penalized VAR estimation with Lasso. Recent advances in high-dimensional statistics have established that it is possible to estimate a VAR model with relatively few samples, if the underlying transition matrix is appropriately sparse. In the context of regression problems, several sparsity-inducing methods have been introduced, arguably the most popular among them being the Least Absolute Shrinkage and Selection Operator (Lasso) (*Tibshirani, 1996*). Recently *Basu and Michailidis (2015)* have established that the Lasso VAR estimates are consistent in high-dimensional settings, i.e., assuming p grows with n , possibly at a faster rate. More precisely, if the number of non-zero elements of the transition matrix $s \ll p^2$, then much fewer sample (than what is required for OLS estimation) is sufficient for consistent estimation of A . An element of the estimated sparse transition matrix, $\hat{A}_{i,j}$, can then be used to denote the edge strength between nodes i and j . *Barigozzi and Brownlees (2013)* proposed a similar Lasso based VAR estimation procedure for network estimation.

The equation-by-equation estimate of Lasso VAR is defined as

$$\hat{A}_i = \operatorname{argmin}_{\beta \in \mathbb{R}^p} \frac{1}{n} \|Y_{:i} - \mathbf{X}\beta\|^2 + \lambda_i \|\beta\|_1, \quad i = 1, \dots, p$$

Here $\|\beta\|_1 := \sum_{j=1}^p |\beta_j|$ is the ℓ_1 -norm penalty, which encourages sparsity in the solution by shrinking smaller coordinates to zero. Using \hat{A} to construct a sparse estimate of network faces the following two issues. The first is the choice of tuning parameters. Lasso VAR minimizes, for every $i = 1, \dots, p$, a residual sum of squared errors (RSS) plus λ_i times the sum of $\sum_{j=1}^p |A_{ij}|$, where λ_i is a tuning parameter controlling the degree of sparsity in \hat{A}_i . Essentially, Lasso augments an OLS minimization with a penalty term that penalizes non-zero coefficients, and higher values of λ_i encourage sparser estimates. Similar to OLS estimates, Lasso penalized least squares estimates of VAR can be obtained by p separate Lasso regressions and it entails selection of p tuning parameters λ_i 's. With limited sample sizes, cross-validation and other data-driven strategies of selecting λ_i 's fail to provide robust guidelines for such choices. The second issue is that Lasso estimates, unlike OLS, do not come with an associated measure of uncertainty. The main reason is that the use of penalty introduces bias in the estimate, which is not easy to quantify in closed form. As a result, developing central limit theorems and associated inference machinery (p-values, confidence intervals) has been a challenge in the practice of Lasso.

Statistical Inference with debiased Lasso VAR. To address these two technical issues, we build upon a recently proposed method of debiasing Lasso estimates (*Javanmard and Montanari, 2014*). It provides a substantial correction to the bias of Lasso and in turn allows assessing uncertainty of the estimated network edges. Also, in order to reduce the degree of subjectivity in tuning parameter selection, this method

uses a theory-driven choice of λ_i 's obtained using the strategy of scaled Lasso (*Sun and Zhang, 2012*). In this work, we extend this method to time dependent data settings.

We start by elaborating on the second point. The theoretical literature of Lasso suggests that Lasso estimates are consistent for a choice of λ_i which scales with the noise standard deviation σ_i , which is unknown in reality (*Bühlmann and Van De Geer, 2011*). The scaled Lasso procedure (*Sun and Zhang, 2012*) suggests a work-around by minimizing a squared error loss function penalized for both large $|A_{ij}|$ and σ_i , and provides an estimate $\hat{\sigma}_i$. Debiased Lasso VAR starts by obtaining equation-by-equation Lasso estimates $\hat{A}_{i\cdot}$, obtained by plugging-in $\hat{\sigma}_i$ in the theory-driven choice of tuning parameters λ_i . In the next step, we conduct a bias correction of \hat{A} using $\tilde{A}_{i\cdot} = \hat{A}_{i\cdot} + \frac{1}{n}M\mathbf{X}'(Y_{\cdot i} - \mathbf{X}\hat{A}_{i\cdot})$, where the matrix M (see Supplementary Discussion 2.7.1 for complete description) is a pseudo-inverse of the sample covariance matrix ⁶. We show that the bias corrected estimates $\tilde{A}_{i\cdot}$ have asymptotically zero mean, finite variance and use the formula $P_{ij} = 2[1 - \Phi(\frac{\sqrt{n}|\tilde{A}_{ij}|}{\hat{\sigma}_i[M\Sigma_X M']_{jj}})]$ (*Javanmard and Montanari, 2014*) to calculate p-values for the hypothesis tests of interest $H_0 : A_{ij} = 0$ vs. $H_A : A_{ij} \neq 0$.

An estimate \hat{A} of the VAR transition matrix can be used to construct a weighted, directed network. An edge is present from node j to node i if A_{ij} is significant at a pre-specified threshold $\alpha > 0$.

The choice of the significance threshold α is important, since constructing the directed network amounts to performing $p(p - 1)$ hypothesis tests. For large p , this requires a correction for multiple testing to avoid the problem of high false positives. The standard Bonferroni criterion for controlling the family-wise error rate (FWER) is the most conservative one, but it suffers from low power. We use a less stringent

⁶Such a bias correction is in the spirit of a single step of Newton-Raphson or Fisher scoring algorithms in classical statistics, with suitable modifications to allow for lack of regularity in high-dimension

criterion of multiple testing, proposed in *Benjamini and Hochberg (1995)*, to control the False Discovery Rate (FDR). FDR is the expected proportion of falsely rejected hypotheses over the total number of rejected hypotheses. Thus, a 20% false discovery rate would imply that, on average, 1 out of 5 selected edges is falsely detected. The procedure was originally proposed for independent test statistics, and its validity for test statistics with positive regression dependency was established in *Benjamini and Yekutieli (2001)*.

Network construction and Centrality with VAR estimates. The topology of a weighted, directed network with edges significant at a level α (after correcting for multiple testing), or its undirected, unweighted skeleton $\mathcal{S}(G)$, can be explored by standard visualization software or by calculating network centrality measures. In Section 2.5, we have used two centrality measures, degree and closeness, of $\mathcal{S}(G)$ to identify central institutions and monitor the degree of connectedness in different components of the US financial sector (e.g. banks, insurance companies and broker dealers). We provide more details on the centrality measures in Section 2.5. However, before applying our model to the data, in the next section we estimate our model on simulated data and contrast it with other measures of systemic risk. This is an important exercise to gain insights on the performance of these measures in stylized settings. Due to the limited number of systemic events, it is almost impossible to empirically validate these measures. The next best alternative is to study the efficacy of these measures on simulated data, which is presented next.

2.4 Simulation Results

In this section, we conduct some simulation experiments to highlight the benefit of our approach over existing measures. In Section 2.4.1, we focus on differences between pairwise VAR and Lasso-VAR in estimating the network structure. In Section 2.4.2, we undertake more extensive simulations to show that the limitations of pairwise approach apply more broadly to other extant measures of systemic risk as well, including MES and CoVaR. The key intuition is similar: these measures estimate the association between the system and a firm, one firm at a time, which stops short of a true system-wide approach. Finally, in Section 2.4.3, we change our data generating process from VAR to allow for contemporaneous correlation structure, and argue that an appropriate statistical method for measuring partial correlation is more suitable than extant pairwise approaches like MES and CoVaR. Thus, our results are not specific to a given set of economic assumptions that result in a lead-lag relationship in the returns of financial institutions. Rather, our model can be used to refine a whole range of statistical estimation in this area.

2.4.1 Granger causality and Network Granger causality

In this section, we conduct a small numerical experiment to demonstrate the advantage of network Granger causal estimates using debiased Lasso VAR (referred to as “LVAR”) over pairwise Granger causal estimates with standard pairwise VAR models. We simulate 100 datasets, each of size $n = 500$, from a 15-dimensional Gaussian VAR(1) model (2.1) (i.e., $p = 15$). The transition matrix A has the following structure: $A_{j-1,j} = A_{j+1,j} = 0.6$, for $j = 2, 5, 8, 11, 14$; $A_{ii} = 0.8$ for $i = 1, \dots, 5$; and $A_{ij} = 0$ otherwise. The noise variance is set to $\sigma^2 = 1$. This model captures a directed network

with five hubs of size 3 each, with 1 central node affecting 2 neighbors. Thus, in this hypothetical network, only 5 of the 15 firms are systemically important.

The average performances of LVAR and pairwise VAR estimates in recovering the true network skeleton are displayed in Figures 2.3 and 2.4. The left Panel of Figure 2.3, shows the skeleton of the true network, with 5 non-overlapping hubs. In the right panel, we plot the “average” network estimated by Lasso VAR (BH correction used with a threshold 20%), where the grayscale of each edge represents the proportion of times (out of 100 datasets) that edge was significant. Similarly, the middle panel shows that “average” network estimated by pairwise VAR (significance threshold set at 5%). The results in the middle panel clearly show that the pairwise VAR model detects too many connections compared to the true network. In this model, the edges are significant either through direct connectivity or through indirect effects of connectivity emanating from a common neighbor. For instance, the estimated pairwise VAR networks select edges between firms 1 and 3, which share a common neighbor 2. Networks estimated using LVAR do not show any such patterns, and thus they are closer to the true network.

Figure 2.4 illustrates that this pattern of selecting high false positive is stable across datasets, and is not an artifact of a few simulated runs. The number of edges selected by pairwise VAR (blue) and debiased Lasso VAR (red) on each of the 100 estimated networks are plotted. The figure clearly shows that pairwise VAR method selects at least 15 edges in all the datasets, while LVAR selects only 10 – 15 edges. This is expected since LVAR takes into consideration the partial dependence between firms while pairwise VAR captures the marginal dependence.

The above results demonstrate the potential limitation of pairwise approach in identifying systemically important institutions. As shown in Figure 2.3, the pairwise

VAR approach identifies all three firms 1, 2 and 3 as central, while in truth only firm 2 is central to the economy. Such misclassification of systemically important institutions can have crucial implications for the detection of risk and a range of policies that depend on systemic risk.

2.4.2 Comparison with MES and CoVaR

In the next simulation experiment, we simulate firm returns from a Gaussian VAR(1) model, where the transition matrix corresponds to the adjacency matrix of a network described in Figure 2.5. To enrich our experiment we now add five firms in the network that are isolated: i.e., not at all connected to the system. The network has $p = 20$ firms, of which $\{1, 2, 3, 4, 5\}$ are isolated, i.e., they are not affected by shocks on the other firms. There are 3 central/risky firms in this universe $\{8, 13, 18\}$, each of which transmits shock to four other firms. Based on $n = 500$ returns simulated from this model, we calculate MES, CoVaR and degrees of different firms in pairwise and Lasso VAR networks. The results are reported in Figure 2.6. The top panel shows that except the five isolated firms, all the firms are deemed as risky in MES, CoVaR and pairwise VAR. Moreover, with a slight exception to MES, the true central firms $\{8, 13, 18\}$ are hard to detect among the 15 connected firms in this universe. In contrast, Lasso VAR captures the true network structure and ranks the three central firms as highly risky compared to the other 15 firms.

2.4.3 Contemporaneous Correlation Structure

In this section, we show that the importance of delineating direct vs. indirect associations amongst firms is prominent even when the connection among firm returns is contemporaneous instead of intertemporal (i.e., the lead-lag relationship). This exer-

cise is also useful in stressing the point that our approach does not depend on whether one takes a strong view on the informational efficiency of the markets or not. To demonstrate this, we generate firm returns from a multivariate Gaussian distribution, where the partial correlation among firms encode the conditional relationship described in the network 2.5. We simulate $T = 500$ returns from this distribution, and report the estimated MES, CoVaR and firm degrees in pairwise VAR in Figure 2.7. We simulate data from a $p = 20$ -dimensional Gaussian distribution with correlated components, where the conditional independence among the nodes follows the network structure in Figure 2.5. In particular, we construct a matrix Θ as follows: for each $j \in \{8, 13, 18\}$, we set $\Theta_{ij} = \Theta_{ji} = 0.5$, where $j \in \{i - 2, i - 1, i + 1, i + 2\}$. For every other pairs $\{i, j\}$, $\Theta_{ij} = 0$. To ensure the positive definiteness preserving the network structure, the inverse covariance matrix is generated as $\Theta + (|\lambda_{\min}| + 0.2)I$, where λ_{\min} is the minimum eigenvalue of Θ . The inverse covariance matrix is contain information on the partial correlations and is routinely used in Gaussian graphical modeling (see Supplementary Discussion 2.7.2 for more details).

Since MES and ΔCoVaR measure contemporaneous association between each firm and the system, these measures are highest for the central firms $\{8, 13, 18\}$, however the firms affected by these three central firms are also close. Since there is no intertemporal dependence, pairwise VAR does not detect any Granger causal relationship as expected. The same holds for LVAR. However, we show that a bias corrected version of Graphical Lasso (*Friedman et al. (2008); Jankova et al. (2015)*), a method for calculating partial correlation in high-dimension, correctly detects the central firms as more risky than the other 15 firms. Similar to the network Granger causality, partial correlation measures the correlation between each pair of firm returns, conditioning on the returns of all the other firms under consideration. The firm pairs (i, j) with strong partial correlation

relationships can be recovered using nodewise regression, i.e., regressing R_i on the returns of all the other firms, and looking at the coefficient of R_j (*Meinshausen and Bühlmann, 2006*). An alternative approach utilizes the fact that the partial correlation structures among the components of a multivariate Gaussian random variable $\mathbf{X} \sim N(0, \Sigma)$ can be obtained from the inverse covariance matrix $\Theta = \Sigma^{-1}$. Based on these connections, the graphical Lasso (Glasso) estimates Θ use a Lasso penalized maximum likelihood method to estimate Θ :

$$\hat{\Theta} := \underset{\Theta \succeq 0}{\operatorname{argmax}} \log \det \Theta - \operatorname{tr}(S\Theta) - \lambda \sum_{i \neq j} |\Theta_{ij}|,$$

where S is the sample covariance matrix, λ is a tuning parameter controlling the degree of sparsity and $\succeq 0$ denotes that the function is maximized over non-negative definite matrices. Both of these approaches are commonly used in the statistics literature to build partial correlation networks from high-dimensional data sets. In recent work, *Brownlees et al. (2015)* used Glasso based estimates to construct a network amongst firms based on their realized volatilities. We use a bias corrected version of Graphical Lasso, recently proposed in *Jankova et al. (2015)*, which provides a measure of uncertainty of the edge weights. We provide further details on the estimation exercise in Supplementary Discussion 2.7.2.

Overall, these simulation results establish the usefulness of our approach in estimating the true network structure. We now proceed with the estimation exercise with actual data on stock returns of large financial firms in the U.S.

2.5 Empirical Application

We estimate the LVAR model to detect the Network Ganger Causality structure on a subset of the data set used by *Billio et al.* (2012b).

2.5.1 Data Description and Summary Statistics

We use monthly returns data from January, 1990 to December, 2012 for three financial sectors, namely banks (BA), primary broker/dealers (PB) and insurance companies (INS) available at the University of Chicago's Center for Research in Security Prices (CRSP) and retrieved from Wharton Research Data Service (WRDS). We denote firms with Standard Industrial Classification (SIC) from 6000 to 6199 as banks, from 6200 to 6299 as broker/dealers and from 6300 to 6499 as insurance companies. We divide the data into 3-year rolling windows, retaining only the institutions that have complete data in that window. To create our final data set, we keep the top 25 institutions in terms of market capitalization in each sector in every time window.

Our final sample covers 225 different institutions spanned over 23 years period. Figures 2.8 and 2.9 show the mean and standard deviation (in %) of monthly stock returns across different sectors in each 3-year rolling window. As expected, the average returns are significantly lower and the standard deviations significantly higher during the 2007-2009 period, compared to any other period in our sample. Another period of significant volatility in the sample is the Russian financial crisis in 1998. Also, looking across sectors, all three experienced stress during the 2007-2009 crisis, whereas around 1998 it was predominantly the broker-dealers (PB) who exhibit high volatility.

2.5.2 Network estimation and Measures of connectedness

In order to estimate our network, we consider the Generalized AutoRegressive Conditional Heteroscedasticity (GARCH(1,1)) as our baseline model for returns of individual firms. This allows us to remove any effect of heteroskedasticity from contaminating our LVAR measure. Since accurate estimation of Granger causal relationships relies crucially on the stationarity of the underlying data generating process (*Lütkepohl, 2005*), raw returns with high heteroskedasticity are not appropriate for constructing Granger causal networks. The approach of using GARCH fitted residuals was also adopted in *Billio et al. (2012b)*. Multivariate GARCH models like Dynamic conditional correlation (DCC) (*Engle, 2002*) were not applicable due to high-dimensionality in our data set with ($n = 36$ time points, $p = 75$ firms), but are potential alternatives to univariate GARCH ones, if the sample size is sufficiently large. We note that by denoting an institution’s return at time t as $R_{i,t}$, a GARCH(1,1) specification implies the following.

$$\begin{aligned} R_{i,t} &= \mu_i + \sigma_{i,t}\epsilon_{i,t}, \quad \epsilon_{i,t} \sim N(0, 1) \\ \sigma_{i,t}^2 &= \alpha_0 + \alpha_1\epsilon_{i,t-1}^2 + \beta_1\sigma_{i,t-1}^2 \end{aligned} \tag{2.2}$$

We estimate the GARCH(1,1) parameters μ_i , $\sigma_{i,t}$, α_0 , α_1 and β_1 for each of the 75 institutions in every time window. Then we fit our debiased Lasso VAR (LVAR) model to the estimated Garch fitted returns, namely $\hat{\epsilon}_{i,t} = \frac{R_{i,t} - \hat{\mu}_i}{\hat{\sigma}_{i,t}}$ in every window. Our LVAR network thus defined has 75 nodes, each corresponding to a financial institution and unweighted non-directional edges such that an edge between institution i and j denotes either that i Granger-causes j , or j Granger-causes i or both, after a BH p-value correction at a 20% threshold level of FDR in the estimated LVAR model.

2.5.3 Comparison of Pairwise and Lasso Penalized VARs

We estimate the model on a rolling basis every month with data from the previous 36-months. Thus we obtain a network structure for every month in the sample. Similarly, following *Billio et al.* (2012b), we estimate pairwise VARs for the 75 largest firms in every time window as before and define unweighted non-directional edges such that an edge between institution i and j denotes either that i Granger-causes j , or j Granger-causes i or both at the 5% level of significance.

In Figure 2.10 we plot the graphs of networks estimated using the pairwise VAR and the LVAR models for two periods overlapping financial crises. The upper and lower panel depict the networks estimated for windows October 1995 - September 1998 and August 2006 - July 2009, respectively. Both types of network plots show high connectivity during crises. However, as expected, the pairwise VAR model estimates a far denser network. In comparison, the LVAR network is sparse and identifies AIG and Goldman Sachs as key central nodes during the 2007-09 period. The benefit of the LVAR model over traditional techniques can be easily seen from these figures. First, it allows us to pin down highly interconnected periods in a cleaner manner and second, it provides a stronger separation between important institutions such as AIG and Goldman Sachs and the rest, compared to the pair-wise model.

Consistent with our simulation results, the pairwise network captures both direct and indirect linkages between the two firms in the real data as well. This in turn results in several false positives. Our refined measure, on the other hand, is able to separate out weaker connections from stronger ones, and hence it provides a more meaningful measure. Since there are limited systemic events during the sample period, it is hard to empirically assess the validity of these models with any reasonable degree of precision. It is, therefore, even more important to rely on statistically principled techniques for

future applications of network models. In the remainder of this section we discuss our results and findings in more details to establish the usefulness of our measure in understanding system-wide connectivity.

2.5.4 Time Series of Summary Statistics

In our first test, we study the evolution of system connectivity based on our measure. In order to do so, we summarize the estimated networks using two primary measures of centrality well known in the network literature, namely degree and closeness.

$$\begin{aligned} \text{Degree of node } i &= \text{deg}(i) = \text{number of edges adjacent to node } i \\ \text{Closeness of node } i &= \frac{1}{\sum_{i \neq j} d(i, j)} \end{aligned}$$

where $d(i, j)$ = shortest path length between node i and j , i.e., number of edges constituting the shortest path between i and j . If there is no path between nodes i and j , then the total number of nodes is used as the shortest path length. While average degree measures the average number of direct neighbors, i.e., connectivity in the network, average closeness measures the shortest number of steps in which a node can be accessed from another node.

Figure 2.11 and Figure 2.12 plot average degree and closeness, respectively of our estimated network over 3-year rolling windows. These time series plots show that connectivity, measured either by count of neighbors or distance between nodes, increases before and during systemically important events. In both figures, we mark a few key events of the last decade at the time window when it is first included in the sample. In both figures we see two bigger cycles, one starting around 1998 and another around 2008. The former coincides with the Russian default and LTCM bankruptcy in late

1998 and the latter marks the financial crisis of 2007-2009. In between the two, there is another prominent cycle of increased connectivity starting around 2002 that coincides with the growth of mortgage-backed securities (e.g., see the pattern in MBS growth over this time period in *Ashcraft et al.* (2010), Figure 3) and the increased connectivity of different sectors of the market through holdings of these securities as well as increased interlinkages through insurance contracts.

The time-series results show that our network measure is sensible in detecting large systemic events. To contrast our measure with pairwise network model, in Fig 2.13 we plot the evolution of connectedness based on the two models. Note that it is not useful to directly compare the number of connections over time based on the two models, since the pairwise VAR has always significantly higher number of connections. A meaningful measure should be based on deviation from historical levels of connections – disproportionate increase or decrease in connectivity measures compared to historical numbers provides more meaningful information on the buildup of systemic risk in the economy. Thus, we scale the degree centrality of both network models in different rolling windows by the historical average of degree centrality over all rolling windows spanning 1990-2012. Figure 2.13 provides the results. Both models are able to detect the 2008-09 financial crisis, however, LVAR model does a much better job around the Russian/LTCM default. It is comforting to see the sharp spike in LVAR model-based connectivity in periods leading up to both the important events during our sample period.

It is clear that the key feature of our model is to separate out relatively stronger connections from the weaker ones. Hence, a key benefit of our approach is cross-sectional in nature, namely our model better identifies firms that are systemically more important than the others in a stressful situation. We had shown this advantage

with simulated data in Section 2.4. Now, we identify the important institutions in real data using our model. In Figure 2.14 we show the list of important firms based on our connectivity measures, and Table 2.1 contains firm names with ticker symbols. Since the estimated networks exhibit different levels of overall sparsity in different time periods, raw degree centrality of a firm is not ideal to capture its relative importance in the system. So in each time period, we take the normalized degree of firms, i.e., $(\text{degree} - \text{average node degree}) / (\text{standard deviation of node degrees})$, as a measure of systemic importance of the firm in that time period. We list firms with highest degree in networks estimated using 3 year historical data starting May, 2007 and then re-estimating the network every two months. We see that AIG emerges as one of the highest degree nodes as early as July, 2008. We also see the increasing connectivity of Goldman Sachs from March, 2009 onwards. These estimates line up well with the anecdotal evidence on the importance of these institutions, especially AIG, during the financial crisis period. More importantly from a regulatory perspective, the separation between AIG and the second most important institution in our network is stark. Figure 2.15 reproduces the figure based on pair-wise VAR. In this model too, AIG and GS come up as important institutions, but the separation between AIG and the next firm is much smaller than our model. Thus, when we separate out all the indirect connections in the network, AIG emerges as a significantly more important institution than what one would conclude based on a model that captures the effect of both direct and indirect connections. Second, our model continues to identify AIG as a relatively more important institution even in 2009-2010 period, compared to the corresponding estimation based on pairwise VAR model. Again, the result shows that there are non-trivial practical implications emanating from the estimation method employed.

2.5.5 Results around the Lehman Brothers Failure Event

We exploit the failure of Lehman Brothers in September 2008 as a shock to the system, and use this event to shed light on the usefulness of our network in detecting interconnected firms. On September 10, 2008 Lehman Brothers puts itself up for sale, but does not find a buyer. The U.S. government refuses to step in and ultimately the firm announced its bankruptcy filing on the eve of September 15, 2008. There was considerable government intervention immediately following its collapse. However, in the short window of time from September 10 – September 16, there was significant ambiguity about the bailout possibility. We expect firms connected to Lehman to experience large negative returns during this period. That is indeed the case based on our network estimation. Lehman has two direct connections in the network – AIG and Cigna. As shown in Table 2.2, AIG experienced large negative returns of -60.8% on September 15. CIGNA had a negative return of -2.9% on the day. Both these firms continue to experience large negative returns till September 18, 2008, when the U.S. government announced a rescue package for AIG. Extending the analysis to the neighbors of Lehman’s neighbors, the Table also produces returns for this event window for firms connected to AIG and CIGNA. They all experience large negative returns on September 15, 2008, with AIG’s neighbors experiencing generally more negative returns than CIGNA’s neighbors. As this analysis illustrate, a useful feature of our model is that we can trace the effect of a negative shock on a firm on the entire network by tracing its effects through the direct linkages. Pairwise analysis doesn’t lend itself to such an experiment due to the confounding indirect effects.

2.5.6 Inter-sectoral Connectivity

Our model allows us to study both within and across sector connectivity. Even since great depression, there has been a number of policy interventions in banking industry that are primarily motivated by concerns about connections across banking, broker-dealer, and insurance sector. A prominent example is the imposition of the Glass-Steagall Act in 1933 that prohibited commercial banks from engaging in investment banking activities, such as underwriting of securities or investment in certain class of securities with their own money or their client's money. Some of the key provisions of the Act were repealed during our estimation period through the enactment of Gramm-Leach-Bliley (GLB) Act of 1999. The GLB Act removed barriers between the commercial banks, broker-dealers and insurance sector. Thus we expect the inter-sectoral connectivity to increase around this period. While the Act itself was finally passed in 1999, the real effect of this act was felt in the market starting from 1998 itself. In 1998, Citicorp, a commercial bank, merged with the insurance company Travelers Group to form a conglomerate combining banking, securities and insurance services under one large group. This merger was in violation of the original Glass-Steagall Act at the time, but after the enactment of GLB Act a year later, it was given a legal status on a retrospective basis. For our network, this is an important event: by law banking, insurance, and broker-dealer sectors are expected to show increased connectivity during this period.

We plot the evolution of inter-sector linkage between the insurance sector and the other two sectors in Figure 2.16. The figure demonstrates that insurance sector became more connected with both the broker-dealer and banking sector in 1998-1999. These results show that our network topology is consistent with the intended consequence of the repeal of Glass-Steagall Act that increased the connectivity across sectors. Overall

our results are consistent with broad changes in the markets and regulations.

2.6 Conclusions

We propose a measure of network connectivity based on a system-wide approach. Unlike extant measures that rely on pairwise approach, we estimate the connections across all firms in a system-wide sense. Such an improvement is important for measures of risk that are designed to detect system-wide effects. While we use measure based on stock returns to illustrate the usefulness of our approach, our model can also be applied to other sensible measures of firm characteristics such as volatility and value-at-risk.

Our simulation exercises highlight the usefulness of taking a systemic approach suggested by our model – it separates out direct linkages from the indirect ones, which in turn allows us to pin down the source of shock propagation in a system. Several policy proposals, such as linking capital requirements to measures of systemic risk, crucially depend on an accurate measure of this risk. Any misclassification, therefore, is likely to be costly to the economy. Our measure minimizes the possibility of such misclassifications. Finally, we apply our method to large financial institutions of the U.S. and show that our model is able to capture both systemic events and systemically important institutions in a meaningful manner.

Figure 2.1: A schematic representation of VAR(1) model with $p = 3$ firms A, B, C. There are 3 network Granger causal effects in the model: $B \rightarrow C$, $B \rightarrow A$, $C \rightarrow B$. However, due to indirect effect through B, there is additional pairwise Granger causal effect $C \rightarrow A$.

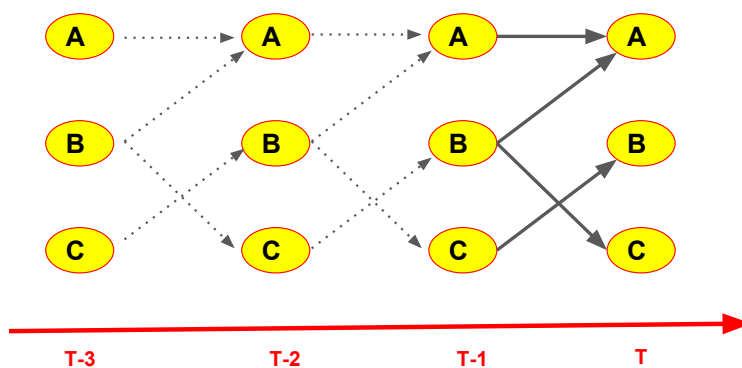
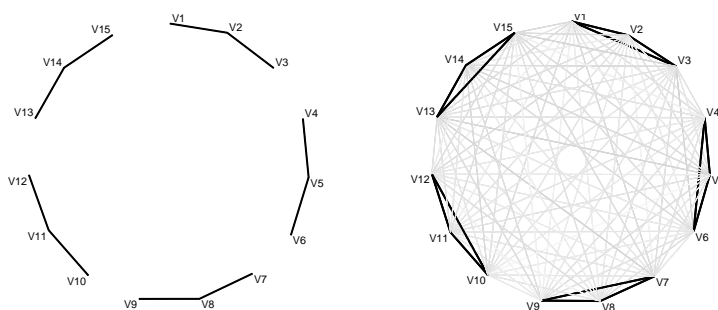
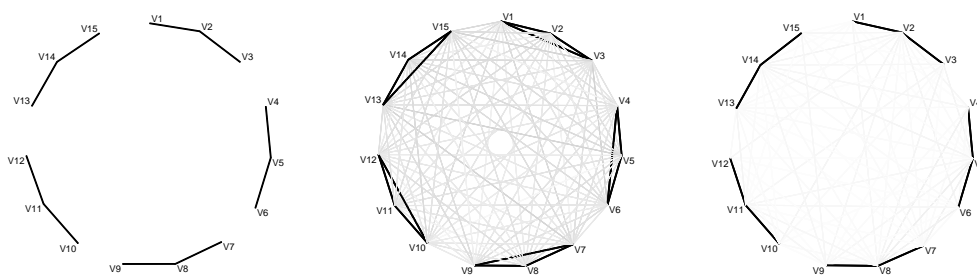


Figure 2.2: Simulation



True network and the network estimated by pairwise GC in a simulated universe with 15 firms. In this universe, there are 5 central firms $\{2, 5, 8, 11, 14\}$ - each affecting two different firms and forming a network with 5 hubs. In addition to the true network edges, the pairwise GC method picks up additional edges between each pair of non-central firms in each hub. The shade of the edges are darker proportional to the number of times they are estimated.

Figure 2.3: A simulated network estimation ($n = 500$, $p = 15$) with pairwise VAR and debiased Lasso VAR (LVAR). The true network (left) has 5 hubs, each of size 3. Pairwise VAR (middle) estimates marginal association and captures indirect effects, and hence the estimated network (middle panel) has 5 complete cycles. Lasso VAR (right), on the other hand, estimates conditional dependence and accurately identifies the structure of the 5 hubs, including the central node and the neighbors. The grayscales of edges represents the proportion of times an edge was detected by Lasso VAR and pairwise VAR in 100 simulated datasets from the true network.



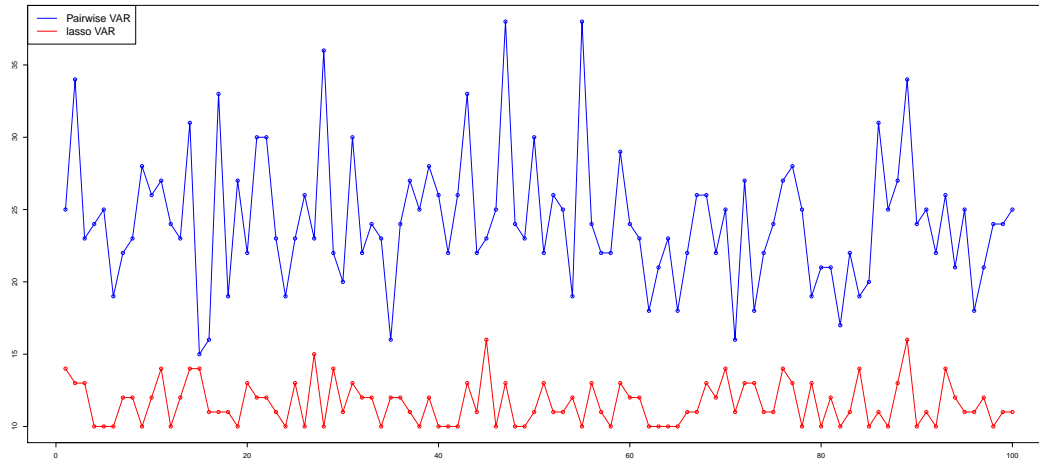
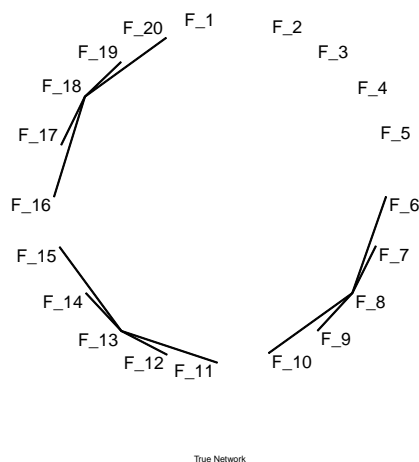


Figure 2.4: Edge discovery in the simulated network estimation problem of Figure 2.3. The total number of significant edges discovered by Lasso VAR and pairwise VAR in 100 simulated datasets from the true network are plotted. Pairwise VAR (blue) selects at least 15 edges in all instances, while debiased Lasso VAR (red) selects much fewer edges, between 10 and 15, consistently across different datasets. The number of edges in the true network is 10, as shown in the left panel of Figure 2.3.

Figure 2.5: True Network with 5 isolated firms $\{1, 2, 3, 4, 5\}$, three central firms $\{8, 13, 18\}$ each with 4 neighbors. The returns were simulated based on a Gaussian VAR(1) model with a transition matrix A with the above network structure. In particular, we set $A_{ii} = 0.7$ for $i = 1, \dots, 20$. Also, for every $j \in \{8, 13, 18\}$ and $i \in \{j - 2, j - 1, j + 1, j + 2\}$, we set $A_{ij} = 0.6 + \eta_{ij}$, where $\eta_{ij} \stackrel{i.i.d.}{\sim} \text{uniform}(0, 0.05)$. For all other pairs $\{i, j\}$, we set $A_{ij} = 0$.



True Network

Figure 2.6: Boxplots of systemic risk measures based on 100 simulated datasets of size $n = 500$ generated from a VAR(1) model described in Figure 2.5. For the pairwise measures MES, ΔCoVaR and pairwise VAR, the first 5 isolated firms have the lowest systemic risk measure. However, the systemic risk measures of the central nodes $\{8, 13, 18\}$ are not significantly different from the peripheral nodes. In LVAR, the degrees of the central nodes are significantly different from the rest, and hence identification of risky nodes is easier.

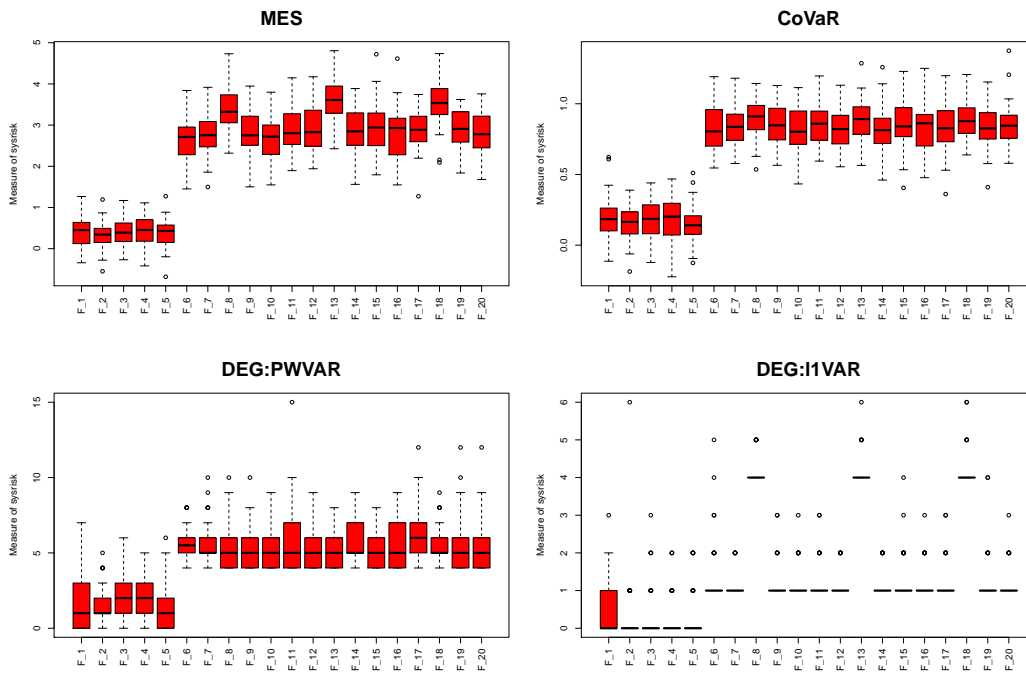


Figure 2.7: Boxplots of systemic risk measures based on 100 simulated datasets of size $T = 500$ with only contemporaneous dependence among nodes. The data are generated from a Gaussian graphical model with a true network structure of Figure 2.5, see Section 2.4.3 for more details. We report the performance of three pairwise measures: MES, ΔCoVaR , pairwise VAR, and a system-wide measure, viz., debiased graphical lasso. For the pairwise measures MES, ΔCoVaR and pairwise VAR, the first 5 isolated firms have the lowest systemic risk measure. However, the systemic risk measures of the central nodes $\{8, 13, 18\}$ are not significantly different from the peripheral nodes. In networks estimated by debiased graphical lasso, the degrees of the central nodes are significantly different from the rest, and hence identification of risky nodes is easier.

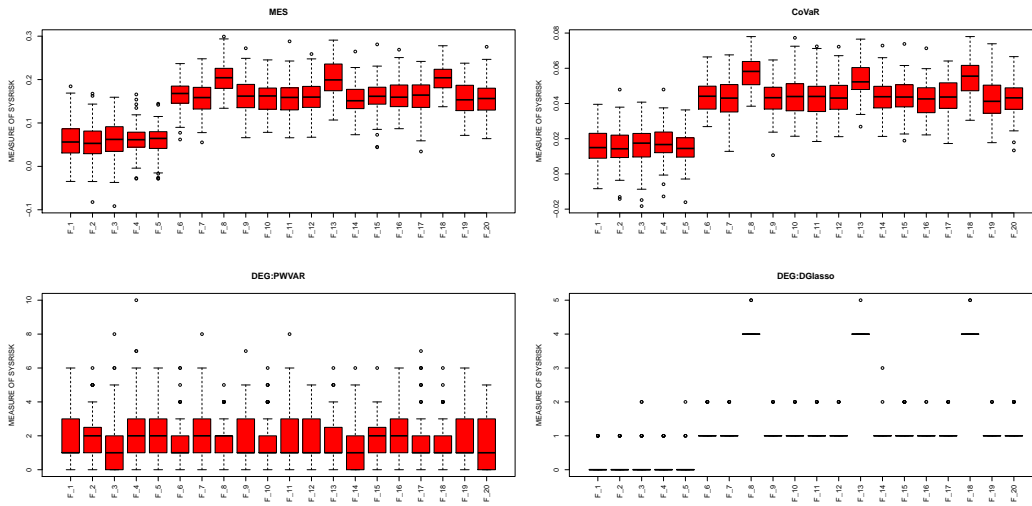


Figure 2.8: Average monthly return of firms used in the empirical analysis of Section 2.5 over 3-year rolling windows spanning 1990 – 2012. In each window, 25 largest firms (in terms of market capitalization) from three sectors - Banks (BA), primary broker-dealers (PB), and insurance firms (INS), are included.

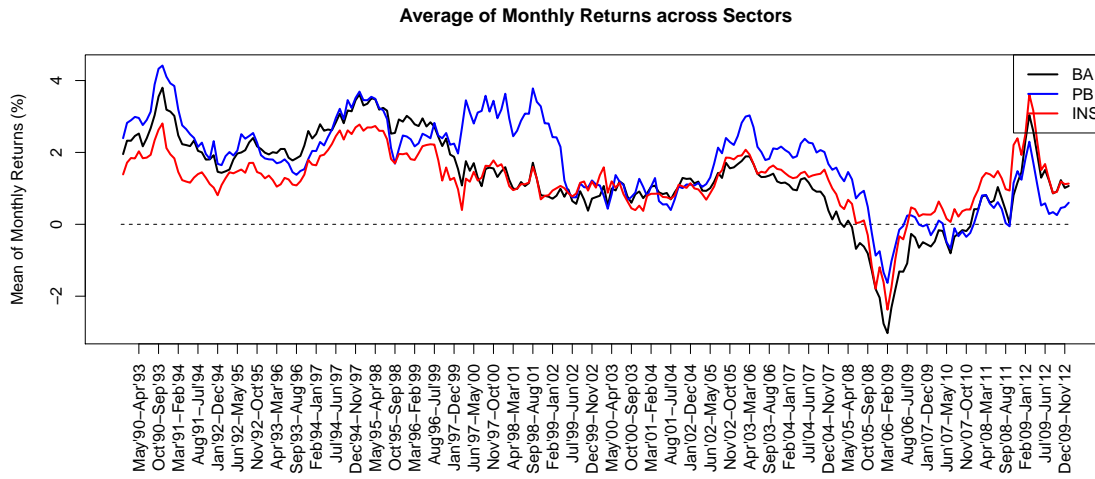


Figure 2.9: Standard deviation of monthly returns of firms used in the empirical analysis of Section 2.5 over 3-year rolling windows spanning 1990 – 2012. In each window, 25 largest firms (in terms of market capitalization) from three sectors - Banks (BA), primary broker-dealers (PB), and insurance firms (INS), are included.

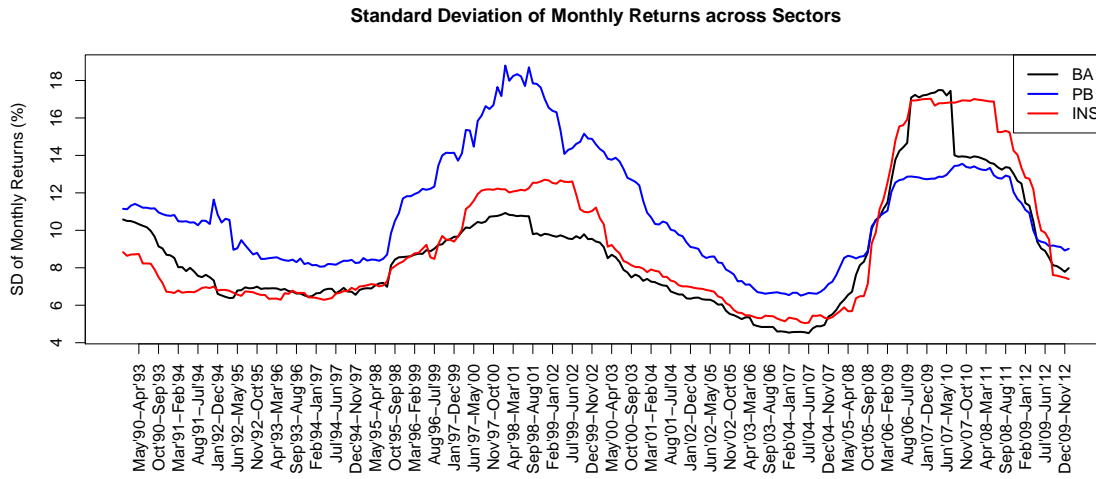


Figure 2.10: Networks estimated by pairwise VAR and lasso VAR on the time horizons (a) Oct 1995 - September 1998, and (b) August 2006 - July 2009. During both crisis periods, networks estimated by Lasso VAR have substantially fewer connections than the networks estimated by pairwise VAR. During the 2007-2009 crisis, AIG, Bank of America and Goldman Sachs emerge as the three highly connected firms in the three sectors - Insurance (INS), Banks (BA) and primary Broker/Dealer(PB).

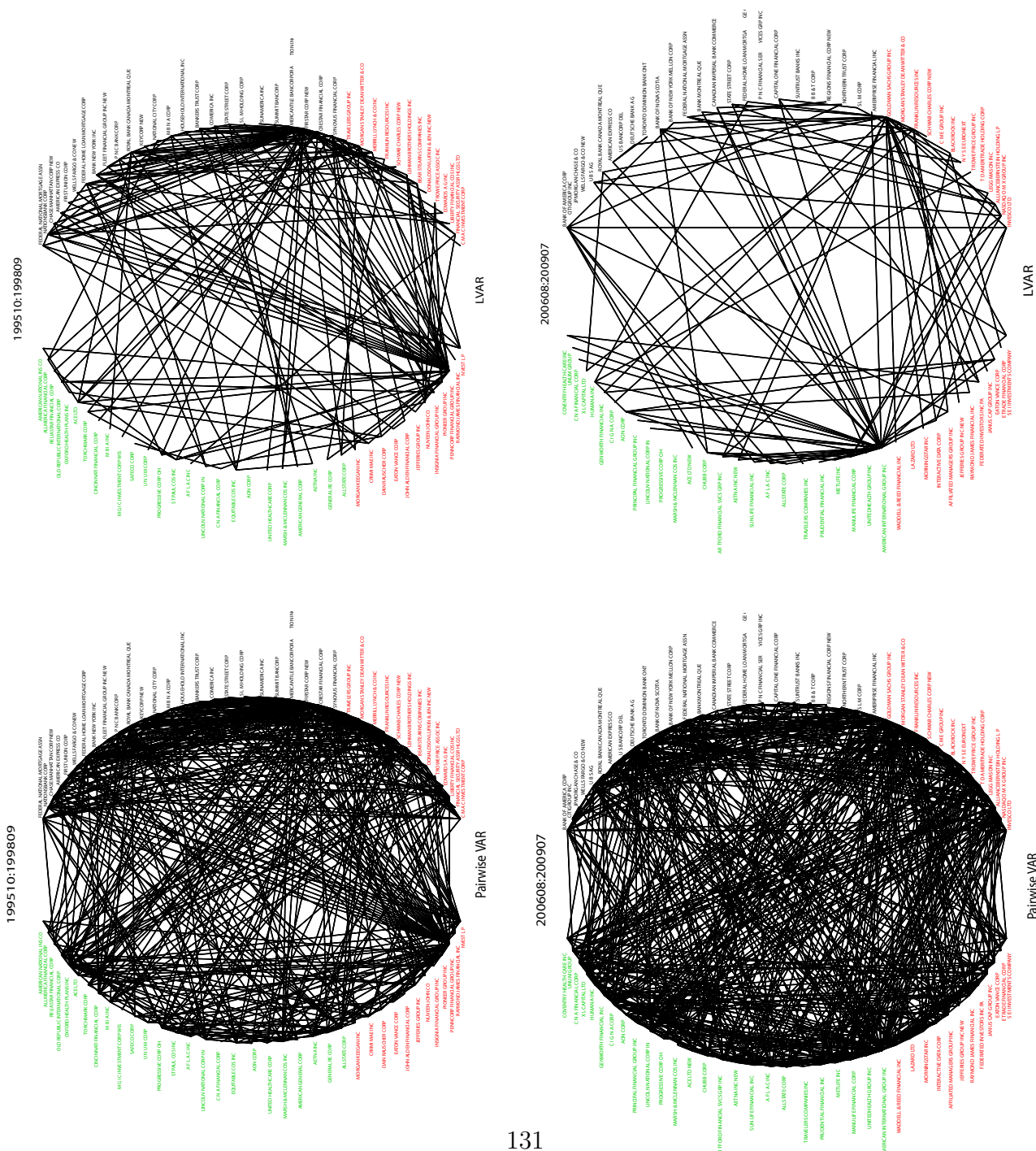


Figure 2.11: Average degree of LVAR networks based on monthly returns of 75 largest firms, estimated separately for 3-year rolling windows spanning 1990 – 2012. Vertical dotted lines indicate important systemic events. Average degree increases around systemic events, showing higher connectivity among financial institutions.

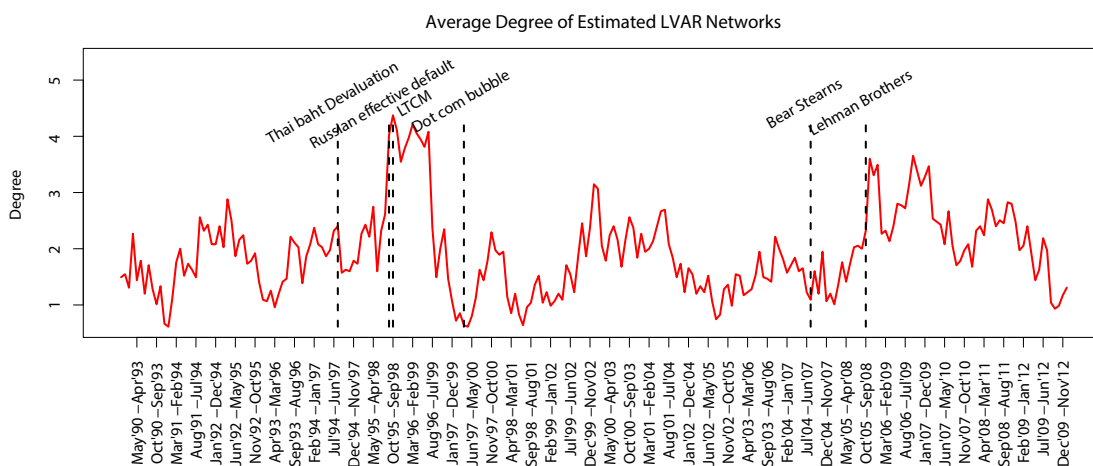


Figure 2.12: Average closeness of LVAR networks based on monthly returns of 75 largest firms, estimated separately for 3-year rolling windows spanning 1990 – 2012. Vertical dotted lines indicate important systemic events. Average closeness increases around systemic events, showing higher connectivity among financial institutions.

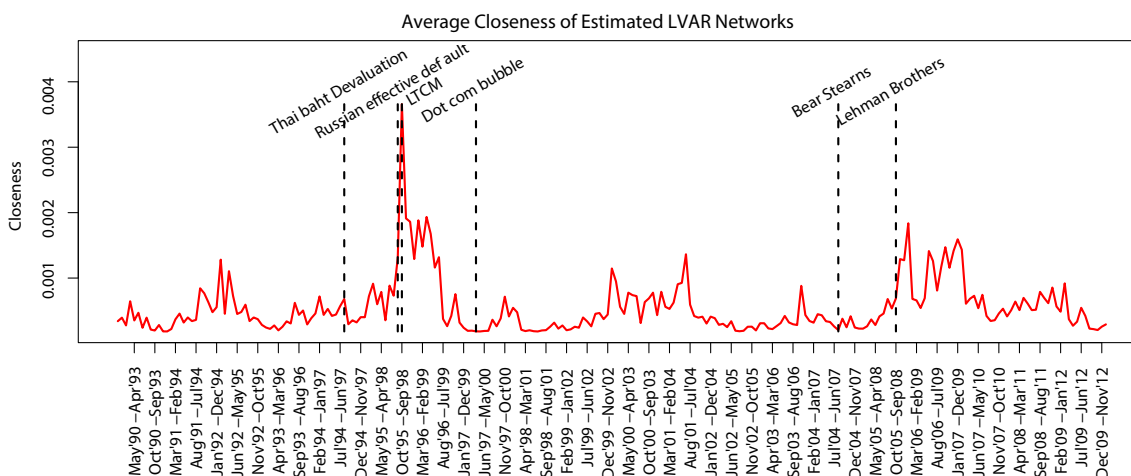


Figure 2.13: Evolution of average degree of return networks, scaled by their historical average (over 1990 – 2012), for LVAR and pairwise VAR. Around LTCM crisis and Russian effective default, connectivity of LVAR networks increased sharply compared to a pairwise VAR network.

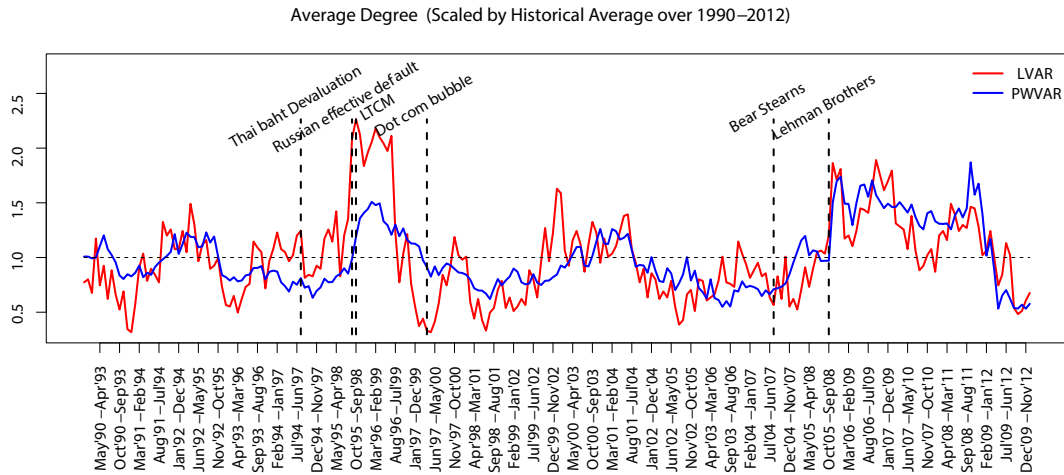


Figure 2.14: Firms with highest number of connections in LVAR networks, estimated using 3 years of monthly returns. The horizontal axis plots the last month of each window, and the vertical axis displays the degree of a firm, standardized by the mean and standard deviation of degrees of all the firms in the network.

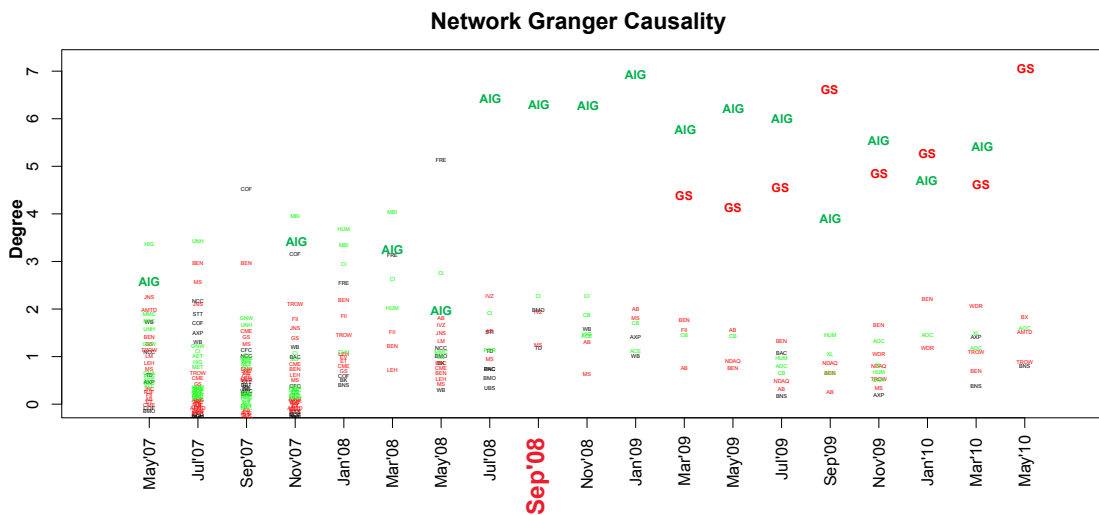


Figure 2.15: Firms with highest number of connections in pairwise VAR networks, estimated using 3 years of monthly returns. The horizontal axis plots the last month of each window, and the vertical axis displays the degree of a firm, standardized by the mean and standard deviation of degrees of all the firms in the network.

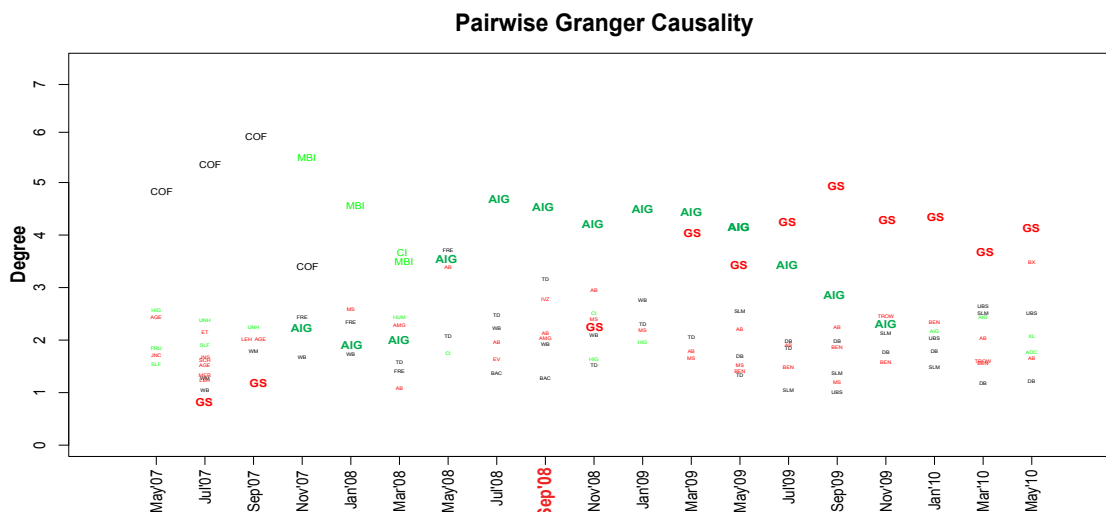


Figure 2.16: Comparison of within- and between- sectoral connectivities for the Insurance sector in estimated LVAR networks. The lines plot, for each of the three sectors, the total number of connections (edges) with firms in other sectors, as a ratio of the number of edges among firms within the sector.

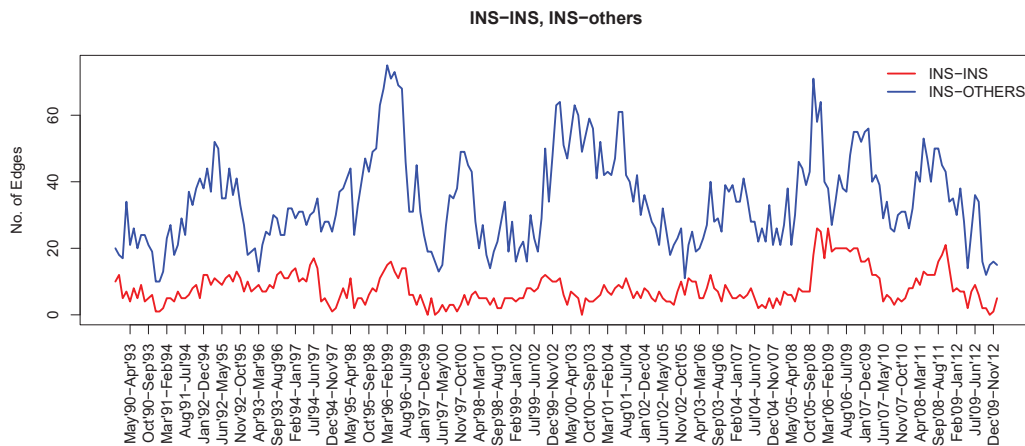


Table 2.1: Firm Names, Sectors and Ticker Symbols

Ticker	Sector	Firm Name
AB	PB	ALLIANCEBERNSTEIN HOLDING L P
AIG	INS	AMERICAN INTERNATIONAL GROUP INC
AMTD	PB	T D AMERITRADE HOLDING CORP
AOC	INS	AON CORP
AXP	BA	AMERICAN EXPRESS CO
BAC	BA	BANK OF AMERICA CORP
BEN	PB	FRANKLIN RESOURCES INC
BK	BA	BANK OF NEW YORK MELLON CORP
BMO	BA	BANK MONTREAL QUE
BNS	BA	BANK OF NOVA SCOTIA
BX	PB	BLACKSTONE GROUP L P
CB	INS	CHUBB CORP
CFC	BA	COUNTRYWIDE FINANCIAL CORP
CI	INS	C I G N A CORP
CME	PB	C M E GROUP INC
COF	BA	CAPITAL ONE FINANCIAL CORP
FII	PB	FEDERATED INVESTORS INC PA
FRE	BA	FEDERAL HOME LOAN MORTGAGE CORP
GNW	INS	GENWORTH FINANCIAL INC
GS	PB	GOLDMAN SACHS GROUP INC
HIG	INS	HARTFORD FINANCIAL SVCS GRP INC
HUM	INS	HUMANA INC
IVZ	PB	INVESCO LTD
JNS	PB	JANUS CAP GROUP INC
LEH	PB	LEHMAN BROTHERS HOLDINGS INC
LM	PB	LEGG MASON INC
MBI	INS	M B I A INC
MS	PB	MORGAN STANLEY DEAN WITTER & CO
NCC	BA	NATIONAL CITY CORP
NDAQ	PB	NASDAQ O M X GROUP INC
STI	BA	SUNTRUST BANKS INC
TD	BA	TORONTO DOMINION BANK ONT
TROW	PB	T ROWE PRICE GROUP INC
UNH	INS	UNITEDHEALTH GROUP INC
WB	BA	WACHOVIA CORP 2ND NEW
WDR	PB	WADDELL & REED FINANCIAL INC

Table 2.2: Lehman Brothers Failure Event

Lehman Brothers Neighbors			
	AIG	CIGNA	S&P500 Return
9/10/2008	-4.7%	1.4%	0.6%
9/11/2008	0.3%	1.9%	1.4%
9/12/2008	-30.8%	0.0%	0.2%
9/15/2008	-60.8%	-2.9%	-4.6%
9/16/2008	-21.2%	-3.9%	1.7%
9/17/2008	-45.3%	-6.2%	-4.7%

Panel A: Returns of Most Connected AIG neighbors

	Invesco Ltd	Suntrust Banks	Morgan Stanley	Bank of New York	Citi
9/10/2008	1.7%	-4.9%	-3.7%	1.5%	-1.1%
9/11/2008	1.9%	1.5%	-0.5%	3.4%	-0.4%
9/12/2008	1.0%	3.0%	-3.8%	0.4%	-3.5%
9/15/2008	-6.6%	-3.0%	-13.5%	-8.5%	-15.1%
9/16/2008	4.4%	6.7%	-10.8%	3.2%	3.3%
9/17/2008	-5.9%	-2.7%	-24.2%	-12.3%	-10.9%

Panel B: Returns of Most Connected CIGNA neighbors

	Bank of New York	Regions Financial Corp	Chubb Corp	Ace Ltd New
9/10/2008	1.5%	-2.7%	2.0%	-0.5%
9/11/2008	3.4%	-1.1%	0.3%	0.3%
9/12/2008	0.4%	5.1%	0.4%	0.8%
9/15/2008	-8.5%	-4.0%	-2.1%	1.2%
9/16/2008	3.2%	5.6%	13.5%	8.5%
9/17/2008	-12.3%	-7.4%	-5.0%	-3.0%

2.7 Supplementary Discussion

2.7.1 Estimation of large VAR models

We discuss statistical issues for estimating VAR models using ordinary least squares (OLS) when the sample size (n) is small compared to the number of time series (p), and describe how Lasso based penalized estimation methods can be used to overcome them. We conclude with a description of our multiple testing correction methods to construct networks based on fitted VAR models.

In low-dimensional problems ($n > p$), the most common method for estimating VAR models is ordinary least squares (OLS) regression of X^t on X^{t-1} (*Lütkepohl (2005)*). Formally, given $n + 1$ observations $\{X^0, X^1, \dots, X^n\}$ from the stationary VAR process (2.1), one forms autoregressive design

$$\underbrace{\begin{bmatrix} (X^{n+1})' \\ \vdots \\ (X^1)' \end{bmatrix}}_{\mathbf{Y}} = \underbrace{\begin{bmatrix} (X^n)' \\ \vdots \\ (X^0)' \end{bmatrix}}_{\mathbf{X}} A' + \underbrace{\begin{bmatrix} (\varepsilon^{n+1})' \\ \vdots \\ (\varepsilon^1)' \end{bmatrix}}_E \quad (2.3)$$

The OLS estimate of the VAR transition matrix A is then obtained by conducting p separate, equation-by-equation OLS regressions to estimate the rows of A . Formally,

$$\hat{A}_{i:}^{OLS} = \operatorname{argmin}_{\beta \in \mathbb{R}^p} \frac{1}{n} \|\mathbf{Y}_{:i} - \mathbf{X}\beta\|^2, \text{ for } i = 1, \dots, p. \quad (2.4)$$

In classical, low-dimensional asymptotics (p fixed, $n \rightarrow \infty$), \hat{A}^{OLS} is a consistent estimate of A and $\sqrt{n}(\hat{A}^{OLS} - A)$ is asymptotically normal with finite variance-covariance matrix. This allows conducting formal hypothesis tests of Granger causality $H_0 : A_{ij} =$

0 vs. $H_1 : A_{ij} \neq 0$, for all $1 \leq i, j \leq p$, and construct a network of significant Granger causal estimates in a system-wide fashion ⁷.

In a high-dimensional setting with $n < p$, equation-by-equation estimation (2.4) with OLS is no longer possible. Even for $p < n$, the overall estimation error $\|\hat{A}^{OLS} - A\|_F^2$ is of the order of $O(p^2/n)$, which means one needs at least $O(p^2)$ samples for meaningful estimation. Unfortunately, without further assumptions on the network structure, this is the minimal requirement since we are indeed estimating p^2 free parameters.

Under assumption of sparsity of the true network A ($\|A\|_0 := \sum_{i,j=1}^p \mathbf{1}[A_{ij} \neq 0] = s$, $s \ll n$), classical *subset selection* procedures like best subset, forward, backward and step-wise regression can potentially be used to replace OLS in (2.4). However, their statistical properties in the $n < p$ setting are unknown, and they are found to be unstable in empirical applications (*Breiman (1995)*). Another alternative to OLS in such situations is *shrinkage* methods like ridge regression which also appears in the literature of Bayesian VAR. Ridge regression shrinks weak coefficients towards zero to reduce the variance of \hat{A} and produce meaningful estimates, but introduces bias in them. More importantly, interpretation of ridge estimates is not obvious since it does not perform explicit variable selection. Also, due to the added bias of ridge regression, inference machinery in high-dimension has not been developed.

Our choice of Lasso (Least Absolute Selection and Shrinkage Operator) is motivated by its ability to provide an attractive middle ground - it shrinks regression coefficients to reduce variance and make consistent estimation possible in high-dimension, and at the same time performs automatic variable selection by setting weaker coefficients exactly to zero. The resulting estimates are sparse and easier to interpret. Similar to ridge,

⁷Note that this is different from the approach of *Billio et al. (2012b)*, who fit separate bivariate VAR models for different pairs of firms (i, j) , $1 \leq i, j \leq p$.

lasso estimates are biased and statistical inference with them remained a challenging problem for a long time. However, recent developments in high-dimensional statistics have provided means to correct the bias and carry out formal tests of significance of Lasso coefficients in a regression problem. We use Lasso, followed by a bias correction, to estimate our VAR model.

Penalized VAR estimation with Lasso: The equation-by-equation estimate of Lasso VAR is defined as

$$\hat{A}_i = \operatorname{argmin}_{\beta \in \mathbb{R}^p} \frac{1}{n} \|Y_{:i} - \mathbf{X}\beta\|^2 + \lambda_i \|\beta\|_1, \quad i = 1, \dots, p \quad (2.5)$$

Here $\|\beta\|_1 := \sum_{j=1}^p |\beta_j|$ is the ℓ_1 -norm penalty, which encourages sparsity in the solution, by shrinking smaller coordinates to zero. The tuning parameter λ_i controls the degree of sparsity in the estimate, larger values of λ_i result in sparser \hat{A}_i .

Note that under the model (2.1) with diagonal Σ_ϵ , equation-by-equation estimate of Lasso VAR indeed coincides with the penalized maximum likelihood estimate (MLE)

$$\hat{A} := \operatorname{argmin}_{A \in \mathbb{R}^{p \times p}} \frac{1}{2n} \|\hat{A} - A\|_F^2 + \sum_{i=1}^p \lambda_i \|A_{i:}\|_1 \quad (2.6)$$

Since the equation-by-equation estimate is equivalent to p separate Lasso estimates, in our discussion we focus on the generic Lasso estimation of a linear model $Y_{n \times 1} = \mathbf{X}\beta_{p \times 1}^0 + \epsilon_{n \times 1}$, given by

$$\hat{\beta} := \operatorname{argmin}_{\beta \in \mathbb{R}^p} \frac{1}{2n} \|Y - \mathbf{X}\beta\|^2 + \lambda \|\beta\|_1. \quad (2.7)$$

For estimating the i^{th} row of A using Lasso, the errors in the above regression take the form $\epsilon = [\epsilon_i^n : \dots : \epsilon_i^1]'$, the true coefficients $\beta^0 = A'_{i:}$, and the penalty λ_i is chosen

based on $\sigma_i = sd(\epsilon_i^1)$ (see next section). The design matrix $\mathbf{X} = [X^n : \dots : X^0]'$ is the same across all p regressions. The facts that the rows of the design matrix are not i.i.d. and the error vector ϵ is correlated with the design matrix X are specific to VAR estimation problems, and violate the assumptions under which statistical properties of Lasso and debiased Lasso have been studied in literature. We provide some new theoretical analysis to justify their validity in the context of VAR estimation.

Choice of tuning parameters: In practice, choosing the “best” tuning parameter λ is cumbersome and depends on the context of the problem. AIC, BIC or Cross-validation (CV) guided choice of λ are commonly used, although they are known to perform poorly in high-dimensional problems, where $n \ll p$. Since our sample size is small, we use a theory-driven, plug-in estimate rather than cross-validation or data-driven strategies. The theoretical choice of $\lambda \propto \sigma \sqrt{\log p/n}$ (*Bühlmann and Van De Geer* (2011)) requires knowledge of the error standard deviation $\sigma = \sqrt{\text{Var}(\epsilon_1)}$, which is seldom available in practice. To mitigate these problems, we use the scaled lasso algorithm in (*Sun and Zhang* (2012)) to obtain an estimate of $\hat{\sigma}$, and choose $\lambda = C\hat{\sigma}\sqrt{\log p/n}$. Scaled Lasso solves the following convex optimization problem

$$(\hat{\beta}, \hat{\sigma}) \equiv \underset{\beta \in \mathbb{R}^p, \sigma > 0}{\text{argmin}} \frac{1}{2\sigma n} \|Y - \mathbf{X}\beta\|^2 + \frac{\sigma}{2} + \tilde{\lambda} \sum_{j=1}^p |\beta_j|. \quad (2.8)$$

with $\tilde{\lambda} = C\sqrt{\log p/n}$, for some constant C that does not depend on model parameters. Scaled Lasso enjoys similar theoretical properties as Lasso in high-dimensional problems, but does not require knowledge of error standard deviation σ in the choice of tuning parameter. Rather, it provides as a by-product an estimate of σ which can be used for follow-up analyses as in hypothesis testing and confidence interval construction for the regression coefficients $\hat{\beta}_j$.

Consistency of Lasso VAR in high-dimension. *Basu and Michailidis* (2015) have established that the Lasso VAR estimates are consistent in high-dimensional settings, i.e., assuming p grows with n , possibly at a faster rate. In particular, under a double asymptotic framework where both $p, n \rightarrow \infty$, $p = O(n^\alpha)$ for any $\alpha > 0$, and the true sparsity $s = o(n)$, it follows from the results of Section 4 in *Basu and Michailidis* (2015) that $\|\hat{\beta} - \beta^0\|^2 = O_P(s \log p/n)$ with a choice of $\lambda \propto \sqrt{\log p/n}$ and the underlying Gaussian VAR process is stable (*Lütkepohl* (2005)). This rate of convergence demonstrates the remarkable advantage of Lasso (also reported in several other works involving i.i.d. data): modulo a cost of $\log(p^2) = 2 \log(p)$ for searching the locations of non-zero coordinates in A , one needs merely $O(s)$ samples to estimate the VAR coefficients, which is the same as if one *a priori* knew the positions of the s non-zero edges and were only estimating the s free parameters of edge strengths. So, for problems where $s \log p \ll p^2$, Lasso VAR achieves comparable estimation accuracy as OLS with much smaller sample size.

Bias Correction of Lasso VAR estimates:

Despite the nice estimation accuracy of Lasso VARs as above, there are two limitations of using it directly for network construction. First, the shrinkage effect of Lasso introduces a bias in estimating the edge strength, which can be potentially large in a finite-sample setting. Second, the Lasso VAR estimates \hat{A}_{ij} do not come with any measure of uncertainty.

Javanmard and Montanari (2014) proposes a methodology to bias-correct the VAR estimates so as to draw statistical inference. Bias correction of nonlinear estimates is a common technique in classical statistics (*Cordeiro and McCullagh* (1991), *Cordeiro and Vasconcellos* (1997)). For high-dimensional regression problems, *Zhang and Zhang* (2014) first proposed a bias correction method for constructing confidence intervals of

the individual regression coefficients. In parallel lines of work, *van de Geer et al. (2014)*; *Javanmard and Montanari (2014)* also proposed bias corrected versions of Lasso for linear regression. For a more detailed discussion of the intuition behind bias correction, we refer the readers to the excellent review article *Dezeure et al. (2015)*.

In order to correct the bias of Lasso VAR estimates, we first construct a matrix M , which can be viewed as an approximate inverse of the sample covariance matrix $\hat{\Sigma}_X = \mathbf{X}'\mathbf{X}/n$. Given a tuning parameter $\mu > 0$ (chosen in the order of $\sqrt{\log p/n}$), the j^{th} row of the matrix M , $1 \leq j \leq p$, is obtained by solving the following convex program

$$\begin{aligned} & \text{minimize} && m' \hat{\Sigma} m \\ & \text{subject to} && \left\| \hat{\Sigma} m - e_j \right\|_{\infty} \leq \mu, \end{aligned} \tag{2.9}$$

where $e_j \in \mathbb{R}^p$ is the vector with 1 at the j^{th} position and zero at all the other coordinates. If any one of the p convex programs is not feasible, the matrix M is set to identity ⁸.

With the new matrix M , for any given $j \in \{1, \dots, p\}$, the debiased Lasso estimate is given by

$$\tilde{\beta} = \hat{\beta} + \frac{1}{n} M \mathbf{X}' (Y - \mathbf{X} \hat{\beta}), \tag{2.10}$$

where $\hat{\beta}$ is a solution of (2.7).

The intuition of debiasing is simple and can be explained in a low-dimensional context assuming M is exactly $\hat{\Sigma}^{-1}$. Let $\delta = \hat{\beta} - \beta$ denote the bias of lasso estimate

⁸Using arguments of Lemma 23 in *Javanmard and Montanari (2014)* together with Proposition 2.4 in *Basu and Michailidis (2015)*, we can show that $\Sigma^{-1} = (\text{Var}(X^1)^{-1})$ is a solution to 2.9 (hence the constrained optimization problem is feasible) with high probability.

$\hat{\beta}$. Then (2.10) can be expressed as

$$\begin{aligned}\tilde{\beta} &= \beta^0 + \delta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(-\mathbf{X}\delta + \epsilon) \\ &= \beta^0 + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\epsilon,\end{aligned}$$

which is identical to the ordinary least squares estimate. Since ϵ is zero mean Gaussian, under suitable regularity assumption on \mathbf{X} which ensures that the variance does not blow up, the second term is asymptotically negligible, making the bias of $\tilde{\beta}$ orders of magnitude smaller than the bias of $\hat{\beta}$. Another way to motivate the debiasing procedure is to view the bias correction step as an approximate Newton-Raphson iterate, since $(1/n)\mathbf{X}'(Y - \mathbf{X}\hat{\beta})$ and $\hat{\Sigma}$ can be viewed as approximate gradient and Hessian of the least-squares loss function evaluated at the current iterate $\hat{\beta}$. The classic method of Fisher's scoring uses a similar one-step update to a consistent estimate to reduce its variance and make it efficient (*Le Cam* (1956)).

The estimation error of debiased Lasso, after proper rescaling, allows the decomposition

$$\sqrt{n}(\tilde{\beta} - \beta^0) = \frac{1}{\sqrt{n}}M\mathbf{X}'\epsilon + \Delta, \text{ where } \Delta = -\sqrt{n}(M\hat{\Sigma} - I)(\hat{\beta} - \beta^0). \quad (2.11)$$

Suppose the tuning parameters λ and μ are chosen to be of the order $\sqrt{\log p/n}$. In a double asymptotic regime $p, n \rightarrow \infty$ mentioned above, Proposition 4.1 in *Basu and Michailidis* (2015) established that $\|\hat{\beta} - \beta^0\|_1$ is $O_P(s\sqrt{\log p/n})$. This, together with (2.9), implies that $\|\Delta\|_\infty$ is of the order $O_P(s \log p/\sqrt{n})$. Hence, the bias term Δ is asymptotically negligible when $s \log p = o(\sqrt{n})$, and it is possible to conduct inference using only the asymptotic distribution of the first term.

Inference with debiased Lasso. We discuss construction of p-values for the hypothesis $H_0 : \beta_j = 0$ vs. $H_A : \beta_j \neq 0$, for a fixed $j \in \{1, \dots, p\}$, under the double asymptotic regime $n, p \rightarrow \infty$ where $s\sqrt{\log p}/n \rightarrow 0$. Leveraging the asymptotic negligibility of the bias term in (2.11), we use the method proposed in *Javanmard and Montanari (2014)* to construct p -values for testing significance of the individual edges A_{ij} . Formally, for every $i, j \in \{1, \dots, p\}$, the p -value for testing

$$H_0 : \beta_j^0 = 0 \text{ vs. } H_A : \beta_j^0 \neq 0$$

is given by

$$P_j = 2 \left[1 - \Phi \left(\frac{\sqrt{n}|\tilde{\beta}_j|}{\hat{\sigma}[M\hat{\Sigma}_X M']_{jj}} \right) \right] \quad (2.12)$$

where $\Phi(\cdot)$ is the standard normal cdf, and $\hat{\sigma}$ is a consistent estimate of error standard deviation σ obtained using scaled Lasso (2.8) with $\tilde{\lambda} := 10\sqrt{2\log p/n}$, as suggested in the theoretical analysis of *Javanmard and Montanari (2014)*.

Network construction with VAR estimates: Using the estimates of p lasso problems as row vectors, we construct our debiased Lasso VAR estimate \tilde{A} . This matrix can be used to estimate the weighted, directed network described in section 2.3. An edge is present from node j to node i if A_{ij} is significant at a pre-specified threshold $\alpha > 0$.

Choice of the significance threshold α is important, since constructing the directed network amounts to performing $p(p-1)$ hypothesis tests. For large p , this requires a correction for multiple testing to avoid the problem of high false positives. The standard Bonferroni criterion for controlling the family-wise error rate (FWER) is the most conservative one, but it suffers from low power. We use a less stringent criterion of multiple testing, proposed in *Benjamini and Hochberg (1995)*, to control

the False Discovery Rate (FDR). False Discovery Rate is the expected proportion of falsely rejected hypotheses over the total number of rejected hypotheses. Thus, a 20% false discovery rate would imply that, on average, 1 out of 5 selected edges is falsely detected. The procedure was originally proposed for independent test statistics, and its validity for test statistics with positive regression dependency was established in *Benjamini and Yekutieli (2001)*.

The Benjamini-Hochberg (BH) procedure works as follows. Suppose we are testing m null hypotheses H_1, H_2, \dots, H_m with p -values P_1, \dots, P_m . Given the sequence of ordered p -values $P_{(1)} \leq \dots \leq P_{(m)}$, the following two-step procedure controls the FDR at a level $\alpha > 0$:

1. find the largest integer $k \geq 1$ such that $P_{(k)} \leq \frac{k}{m}\alpha$;
2. reject all null hypotheses $H_{(i)}$, for $i = 1, \dots, k$.

The topology of a weighted, directed network with edges significant at a level α (after correcting for multiple testing), or its undirected, unweighted skeleton $\mathcal{S}(G)$, can be explored by standard visualization software or by calculating network centrality measures described in section 2.5.

The complete algorithm for calculating weighted adjacency matrix \tilde{A} based on debiased Lasso VAR is described in Algorithm 1.

2.7.2 Estimating Contemporaneous Dependence with debiased graphical Lasso

We assume the stock returns of p firms across n time points, after appropriate transformations (log, GARCH filter etc.) to reduce nonstationarity, are stored in a

Algorithm 1: Network GC using Debiased Lasso VAR

Input: Data: $\{X^0, \dots, X^n\}$, $X^t \in \mathbb{R}^p$, upper bound on false discovery rates (FDR): α
 $\mathbf{X} \leftarrow [X^{n-1} : \dots : X^0]'$
for $i \leftarrow 1$ **to** p **do**
 $Y \leftarrow [X_i^n : \dots : X_i^1]$
 Estimate noise standard deviation $\hat{\sigma}_i$ using scaled Lasso (2.8)
 Set tuning parameter of Lasso $\lambda \leftarrow \hat{\sigma}_i \sqrt{\log p/n}$
 Calculate Lasso VAR estimate $\hat{A}_{i\cdot}$ using (2.7)
 Calculate debiased Lasso VAR estimate $\tilde{A}_{i\cdot}$ using (2.10)
 for $j \leftarrow 1$ **to** p **do**
 | Calculate p -value P_{ij} for testing $H_0 : A_{ij} = 0$ vs. $H_A : A_{ij} \neq 0$ using (2.12)
 end
end
Adjust p -values P_{ij} , for $1 \leq i, j \leq p$, for multiple testing using Benjamini-Hochberg procedure, controlling for FDR at α
Set $\tilde{A}_{ij} \leftarrow 0$, for all i, j with $P_{ij} \geq \alpha$
Output: Estimated weighted adjacency matrix \tilde{A}

$n \times p$ matrix X , where X_{ij} denotes the return of firm j at time point i . We center the columns of X to have zero mean and unit variance.

Assuming the returns are independent across time, and the p -dimensional vector of returns follow a $N(0, \Sigma)$ distribution, returns of firms i and j are conditionally independent given the rest of the firms if and only if their partial correlation is zero. Since $\Theta = \Sigma^{-1}$ contains partial covariances between firm returns, returns of firms i and j are partially uncorrelated if and only if $\Theta_{ij} = 0$. Hence, the set $E = \{(i, j) | \Theta_{ij} \neq 0\}$ can be used as the set of edges of a graph among the p firms. This procedure is also known as Gaussian graphical modeling.

In classical low-dimensional setting (p fixed, $n \rightarrow \infty$), the maximum likelihood estimate of Θ is given by S^{-1} , where $S := X'X/n$ is the sample covariance matrix. In high-dimensional setting ($n \ll p$), S is not invertible and the MLE is not uniquely defined. In such cases, under sparsity assumption on Θ , the graphical Lasso (Glasso) estimate (*Friedman et al. (2008)*) $\hat{\Theta}$ is defined as the minimizer of penalized negative

log likelihood

$$\hat{\Theta} = \underset{\Theta \succeq 0}{\operatorname{argmin}} \operatorname{tr}(S\Theta) - \log \det(\Theta) + \lambda \sum_{i \neq j} |\Theta_{ij}|,$$

where λ is a tuning parameter controlling the level of sparsity in $\hat{\Theta}$, and $\Theta \succeq 0$ indicates that we minimize over the set of nonnegative definite matrices.

The Glasso estimate is known to be consistent for Θ in high-dimensional settings, as long as Θ is sufficiently sparse (*Ravikumar et al. (2011)*). However, just like Lasso, the Glasso estimate is also known to be biased, and formal statistical inference (confidence intervals, hypothesis testing) with $\hat{\Theta}_{ij}$ is not possible without correcting the bias.

The debiased graphical Lasso (DGlasso), proposed recently in *Jankova et al. (2015)*, corrects the bias of Glasso and provides a method for formally testing presence or absence of an edge between firms i and j ($H_0: \Theta_{ij} = 0$ vs. $H_A: \Theta_{ij} \neq 0$). Below we provide a brief description of DGlasso and refer the readers to *Jankova et al. (2015)* for more details.

Since columns of X are scaled to have zero mean and unit variance, we set $\lambda = \sqrt{\log p/n}$, as suggested in *Jankova et al. (2015)*. Starting with the Glasso estimate $\hat{\Theta}$ and the sample covariance S , the debiased Glasso estimate is defined as

$$\hat{T} = \operatorname{vec}(\hat{\Theta}) - \hat{\Theta} \otimes \hat{\Theta} \operatorname{vec}(S - \hat{\Theta}),$$

where $\operatorname{vec}(A) = [A_{11}, \dots, A_{p1}, \dots, A_{1p}, \dots, A_{pp}]'$ is a vector formed by stacking the columns of a $p \times p$ matrix A , and $A \otimes B = ((A_{ij}B))_{1 \leq i, j \leq p}$ is the $p^2 \times p^2$ Kronecker product of matrices A and B . Similar to the bias correction of Lasso described in Supplementary Discussion 2.7.1, the above bias correction can also be viewed as an approximate Newton-Raphson step.

Under some regularity conditions on Θ , *Jankova et al. (2015)* established that the

entries of the debiased estimate \hat{T} have the following asymptotic distribution

$$\sqrt{n} \left(\hat{T}_{ij} - \Theta_{ij} \right) / \hat{\sigma}_n \xrightarrow{d} N(0, 1), \quad \hat{\sigma}_n^2 := \hat{\Theta}_{ij}^2 + \hat{\Theta}_{ii} \hat{\Theta}_{jj}.$$

Leveraging this asymptotic distribution, we can formally test presence or absence of individual edges in the Gaussian graphical model

$$H_0 : \Theta_{ij} = 0 \text{ vs. } H_A : \Theta_{ij} \neq 0$$

and calculate p -values using the formula $1 - \Phi \left(\sqrt{n} |\hat{T}_{ij}| / \hat{\sigma}_n \right)$, where $\Phi(\cdot)$ is the cumulative distribution function of standard normal density.

The network of partial correlations among the returns of p firms can be constructed using only statistically significant edges after correcting for multiple comparisons using Benjamini-Hochberg procedure described in Supplementary Discussion 2.7.1. Unlike the directed network constructed using the transition matrix of a VAR model, the network of contemporaneous relationships is undirected since Θ is already a symmetric matrix. So we can work with the estimated network directly and calculate centrality measures.

2.7.3 Computing debiased Lasso and Glasso

The simulation and real data analyses in this paper using the statistical software R. We calculated debiased Lasso using the R codes available on the webpage of the authors of *Javanmard and Montanari* (2014) at <http://web.stanford.edu/~montanar/sslasso/> with the default choices of tuning parameters, and implemented the algorithm of *Jankova et al.* (2015) for debiased graphical Lasso ourselves. We used the R function `p.adjust()` to implement the Benjamini-Hochberg procedure for multiple testing

corrections. For the empirical analysis, univariate GARCH models were fitted using R package `fGarch`.

CHAPTER III

Socioeconomic Status and Macroeconomic Expectations

3.1 Introduction

Individuals' choices of consumption, saving, and investment depend on expectations about future macroeconomic conditions. As *Mankiw et al.* (2003), *Souleles* (2004), *Puri and Robinson* (2007), *Dominitz and Manski* (2007) and others have shown, there is substantial disagreement between individuals in their forecasts. Such heterogeneity can have important effects on asset prices and macroeconomic dynamics (e.g., *Sims* (2008), *Geanakoplos* (2009), *Piazzesi and Schneider* (2012), *Guzman and Stiglitz* (2015)). Consumption and investment choices induced by differences in beliefs further may have welfare consequences (*Brunnermeier et al.* (2014)). Yet the origins of this disagreement are still not well understood.

In this paper, we show that heterogeneity in macroeconomic expectations is associated with individuals' socioeconomic status (SES), measured by income and education. Experimental evidence suggests that the degree of economic adversity that people have faced influences their beliefs about the opportunity set available to them. Specifically,

Kuhnen and Miu (2017) find that experimental subjects coming from high SES backgrounds form more optimistic beliefs about risky assets' outcome distributions, relative to low SES subjects, particularly when those assets are likely to have high future payoffs, and are more likely to invest in those assets. We build on this experimental work by analyzing the relationship between SES and people's level of optimism about macroeconomic conditions in a large sample of U.S. adults, recruited monthly over the past three decades to participate in the Michigan Survey of Consumers (MSC).

We find that expectations regarding future stock market returns, the national unemployment rate, and general business conditions are all more optimistic for individuals with higher socioeconomic standing, as measured by their relative income rank within their age group in a given year, and by their level of education. These differences in beliefs are substantial, even after controlling for other demographic characteristics, age cohort effects, and survey time fixed effects. For example, people in the highest income quintile have macroeconomic expectations that are more optimistic by a third of a standard deviation relative to the expectations of people in the lowest income quintile. Having a college degree corresponds to an increase in macroeconomic optimism of roughly one tenth of a standard deviation. In the assessment of the probability that the stock market will experience a gain over the next 12 months, which is one of the dimensions of the optimism index we examine here, there is a spread of 15 percentage points between the probability assessed by people in the bottom quintile of income and those in the top quintile, and a spread of 7 percentage points between the expectations of those without and those with a college education. We further show that the heterogeneity in macroeconomic beliefs across SES categories is pro-cyclical. During recessions the gap in beliefs expressed by people from different SES categories diminishes considerably, by as much as two thirds, as higher SES individuals exhibit a

sharper decline in optimism about economic conditions.

We then investigate why these SES-related differences in expectations exist, and provide evidence that extrapolation from personal circumstances, in a manner similar to the "local thinking" framework proposed by *Gennaioli and Shleifer (2010)*, is a mechanism that is in part responsible for these effects. We show that higher SES individuals become relatively more likely to experience declines in their personal economic situation when recessions arrive, as measured by their reports regarding their personal finances, the business-related news that they find salient, and the objective economic changes in their county of residence. Accounting for these recent developments in people's economic circumstances leads to a significant reduction in the observed wedge in the macroeconomic expectations of individuals with different levels of income or education, across good and bad economic times.

Moreover, we document that differences in beliefs associated with people's socioeconomic standing help explain their economic behavior. Since the MSC offers data on beliefs about macroeconomic conditions, as well as information about people's choices, such as stock market investment decisions and attitudes towards purchasing homes, durables or cars, we can quantify the effect of SES through the beliefs channel on these choices. We find that, while SES measures like income or education on their own directly predict the interest in investing in stocks, or buying homes, durables or cars, there exist indirect effects of income and education through the belief channel that account for a significant fraction of the total effect of the SES variables on these decisions – for example, about 14% in the case of home buying attitudes. We also specifically analyze stock market investment decisions and beliefs regarding stock returns in particular, and show that SES-induced beliefs account for a significant fraction, up to 17%, of the total effect of the SES variables, namely, income and education, on the decision

to invest, and on the share of income invested in equities.

The results in this paper can help shed light on the empirical pattern documented by *Vissing-Jorgensen* (2003), *Campbell* (2006) and *Calvet et al.* (2007), namely, that U.S. and European households with lower education, income or wealth are less likely to participate in the stock market. For example, as of 2013, 51% of U.S. households had no stock market investments. For households in the bottom quintile of the income distribution, 89% had no stock holdings, while for those in the upper quintile, more than 82% had such holdings.¹ The causes of these substantial differences in the investment choices of households across the socioeconomic spectrum are still unclear. Standard explanations involve participation costs (*Vissing-Jorgensen* (2002)), but they still appear to leave a substantial part of the non-participation unexplained (*Andersen and Nielsen* (2011)). Beliefs could be part of the explanation for why some individuals do not participate: whatever the actual cost or perceived cost of participation, low expectations lead to low perceived benefits from participation and hence to low rates of participation. Our findings suggest that lower SES households have less optimistic beliefs about the possible outcomes of risky investments, making it less likely for these households to invest in equities.

Stock market non-participation can imply welfare losses for households, as discussed in *Calvet et al.* (2007). Thus, low macroeconomic expectations can have welfare consequence for low SES individuals. Moreover, non-participation of low SES households may contribute to increasing wealth inequality. By limiting their investment opportunity set, the non-participating low SES households may perpetuate their disadvantaged financial position. *Favilukis* (2013) presents a general equilibrium model

¹Survey of Consumer Finances Chartbook, p. 507-510, issued by the Federal Reserve Board in September 2014, available at <http://www.federalreserve.gov/econresdata/scf/files/BulletinCharts.pdf>.

in which higher rates of stock market participation of less wealthy households would shrink wealth inequality.

Low expectations about future business conditions or unemployment can induce individuals from low SES backgrounds to have low levels of investments along other dimensions also, such as in terms of pursuing higher education, better health, or starting a new business. While there is no direct evidence for this implication of our work, existing relevant findings seem to support it. For example, *Kearney and Levine* (2016) document that children from lower SES families are more likely to drop out of high school, relative to their better-off peers, and attribute this to more pessimistic subjective estimates of the likelihood of economic success among lower SES individuals.

Our work is related to an emerging literature showing that individuals' macroeconomic expectations are "local" in the sense that they are driven by personal circumstances that are specific to an individual or a group of people. While our focus is on an individuals' current economic situation, which is strongly influenced by a person's history of idiosyncratic shocks and initial conditions, earlier work has found links between the macroeconomic history that individuals of a given cohort have experienced, and their expectations and investment decisions. Individuals in cohorts that experienced bad macroeconomic conditions subsequently avoid risky financial choices, either as investors (*Malmendier and Nagel* (2011)) or as managers (*Malmendier and Tate* (2005), *Malmendier et al.* (2011)). Evidence in support of this belief channel is provided by *Malmendier and Nagel* (2015), who find that differences in inflation experiences across cohorts strongly predict differences in the expectations of these cohorts regarding future inflation levels. Experimental evidence in *Kuhnen* (2015) shows that individuals faced with sequences of negative payoffs form overly pessimistic beliefs about the quality of the available investments. *Kuchler and Zafar* (2016) show that individuals'

expectations about national U.S. house prices depend on their personally experienced house price history in their local geographic area, and expectations about the national unemployment rate are influenced by personal experiences of unemployment.²

A common thread in these studies is that expectations about a macroeconomic variable (say, house prices) are related to personal experiences of the realized “local” (cohort-specific or geographically local) history of the same variable. In contrast, the effect that we study is one where a person’s own economic situation is correlated with a broad range of macroeconomic expectations. In other words, we find that a person’s own economic situation appears to be associated with a general macroeconomic optimism or pessimism that is not specific to a particular macroeconomic variable.

Our paper is also related to the recent work on extrapolative beliefs in financial markets. *Greenwood and Shleifer* (2014) document that investor expectations about stock market returns tend to be extrapolative, as they are positively correlated with past stock market returns, and with the level of the stock market. *Barberis et al.* (2015) propose a consumption-based asset pricing model in which some investors form beliefs about future price changes in the stock market by extrapolating past price changes, and show that this model yields predictions that match data well, for example, that high price-to-dividends ratios predict poor subsequent stock market performance, or that stock prices are more volatile than would be justified based on rational forecasts of future cash flows. *Gennaioli et al.* (2015) develop a model of beliefs in financial markets in which investors attach excessive probabilities to states of the world that are representative for the news they observe. This model generates purely belief-driven boom-bust cycles. Our contribution to this literature is to highlight that there may

²*Amonlirdviman* (2007) documents that people with low income or education are more pessimistic about their own personal situation, and presents a model where these individuals suffer from low self-control, and the optimal response to self-control problems is to become defensively pessimistic about one’s future prospects.

be differences in the cross-section of investors with respect to the information set they extrapolate from, and thus, in the volatility of their expectations.

3.2 Data

Our data span the period 1980-2014, at a monthly frequency. Each month, approximately 400 individuals are recruited for the Michigan Survey of Consumers, and are asked to express their beliefs about future values of several macroeconomic variables. The survey is based on a nationally representative group of respondents, sampled using landline and cellular phone numbers (*Curtin and Dechaux (2015)*). In our analysis, we weight observations with the household sample weights provided by the MSC. These sample weights adjust, among other things, for differential non-response by demographic characteristics.³

In total, there are 171,911 person-month observations in our sample. The macro belief variables we study are *PSTK*, *BUS12*, *BUS5*, *BEXP* and *UNEMP*. Table 3.1 presents the survey questions used to measure the belief variables, and the respondents' possible answers. *PSTK* is the respondent's subjective probability that the US stock market will have a positive return over the next 12 months. *BUS12*, *BUS5* and *BEXP* measure expectations about the evolution of the overall business environment over the following 12 months or 5 years, and *UNEMP* measures expectations about the evolution of the national unemployment rate over the following 12 months. We rescale the belief variables except *PSTK* to vary between -1 to 1, such that higher values mean optimism. To calculate an aggregate measure of macroeconomic optimism, we standardize each of

³*Curtin et al. (2002)* investigate the role of survey non-response on expectations collected by the MSC, and find that demographic characteristics, including income and education, do not have sizeable effects on the probability of agreeing to be part of the survey. Moreover, the authors find no evidence that the likelihood of participating in the survey is a function of the respondents' macroeconomic optimism.

these individual beliefs, and average the standardized values. Because *PSTK* is only available starting in June 2002, *OPTINDX* is the average of four standardised beliefs (*BUS12*, *BUS5*, *BEXP* and *UNEMP*) prior to that time, and it is the average of five standardised beliefs (*BUS12*, *BUS5*, *BEXP*, *UNEMP*, and *PSTK*) after that month.

We choose income and education as indicators of the socioeconomic status of households. We restrict our analysis to individuals 24- to 75-years old, because information on income or college degree completion may not be meaningful SES measures for very old or very young adults. Next we create quintiles of real income (in 2014 dollars) within each year and age group (25-29, 30-34, .. 70-74), which we label *Income rank*. We use this as one the socioeconomic status variables because relative income compared to peers may matter more than dollar income, but we obtain broadly similar effects if we use dollar income rather than income rank. *College Degree* is a binary variable which takes value 1 if the respondent has at least a college degree.

To measure recent changes in an individual's personal economic situation, we use three variables. First, we use the variable *1-yr Change in Personal Situation*, provided in the Michigan survey for each respondent, which takes values -1, 0 or 1 if the individual reports being worse off, the same, or better-off than a year ago, in terms of their personal finances. As a simpler version of this variable, we also create an indicator called *Worse off*, equal to 1 if the individual reports that their personal finances are worse than one year before. Second, we use the measure *Amount of good news*, also available in the survey, which indicates how many pieces of good business-related news the respondent was able to recall when interviewed. The possible values are 0, 1 or 2. Finally, for a more objective measure of changes in the individual's economic environment, we use data from the Bureau of Labor Statistics on the unemployment level in

the county when the respondent resides, in the month preceeding the survey.⁴

Table 3.2 presents summary statistics for the variables that capture the personal economic situation, beliefs, and household economic choices of the individuals in the sample. In our data, 35.3% of people have completed at least a college degree. The median real household income (in 2014 dollars) of the participants in the survey is \$57,429, but there are clear outliers in the income distribution, as can be seen in Table 3.2. The average value for the overall amount a person has invested in equities as of the time of the survey is about 85% of the annual income of that individual.

Given the construction of the aggregate belief measure *OPTINDX* as a mean of standardized variables, in our sample spanning 1980-2014 the average *OPTINDX* is close to zero. The average estimates for *BUS12* and *BUS5*, which are beliefs regarding whether there will be good or bad economic times over the next 12 months or 5 year, are 0.014 and -0.06, respectively. Given that the scale for these two variables spans -1 to 1, these averages indicate that expectations about future economic times have not been overly pessimistic or overly optimistic during the 34 years studied here. The same holds true for *BEXP*, the belief regarding general business conditions over the next year, whose average in the sample is 0.096. The belief regarding whether unemployment will be lower or higher over the next year, *UNEMP*, has the most negative sample average, -0.183, indicating that survey participants were the most pessimistic about this particular aspect of future economic conditions. During 2002-2014, the time frame for which this measure is available, the average estimate of *PSTK*, the probability that the U.S. stock market would have a positive return in the next 12 months, is 48.3%, with a standard deviation of 29.3%.

⁴Because the county of residence is not publicly available in the Michigan survey, we had the county-level information merged in by the staff who oversee this survey, but the resulting dataset that we can use does not have the actual county identifiers. The county level data could only be merged in for MSC observations during 2000-2014.

We also use several variables that capture the individuals' decisions regarding stock market investments, namely whether they invest in equity (*Invest*), as well as the share of income invested in the stock market (*Invest Share*), and their attitudes at the time of the survey towards buying a home (*HOM*), buying durables (*DUR*) or cars (*CAR*). About 62% of individuals in our sample participate in the stock market, and on average responses regarding whether it is a good time to purchase a home, durables or cars are positive. For example, the variable *HOM*, which can take values of -1, 0 or 1, indicating either negative, neutral or positive attitudes towards buying a home, has an average of 0.415, and thus is more tilted towards the positive end of the response scale.

3.3 Results

3.3.1 Main results

Our main findings are that higher SES households have more optimistic expectations about macroeconomic conditions, but the SES-related gap in expectations narrows significantly during recessions. Both can be gleaned from the patterns in expectations across SES levels, over time, shown in Figure 3.1. The figure documents that during 1980-2014, higher income and higher education individuals had more optimistic beliefs about future macroeconomic conditions, relative to lower income and lower education individuals. Moreover, the disagreement between households of different SES levels changed over time, as the gap in expectations between the high and low SES individuals diminished during recessions. Thus, the data in Figure 3.1 indicate that the heterogeneity in this aggregate index of macroeconomic optimism across SES levels is pro-cyclical.

Looking specifically at expectations about future stock market returns, the evidence in Figure 3.2 shows that the heterogeneity in beliefs regarding stock market returns across SES levels is similar to that shown by the general optimism index. Namely, higher income and higher education individuals have more optimistic expectations about the stock market return being positive over the following year, and the gap in the expectations of high and low SES individuals is pro-cyclical.

In figures 3.6 through 3.9 in the Supplementary results we document that there exists an SES-induced wedge in beliefs for each component of the optimism index *OPTINDEX* (aside from *PSTK*), namely, *BUS5*, *BUS12*, *BEXP* and *UNEMP*, and that recessions lead to a lower SES-related gap for each of these types of macroeconomic expectations.

We further investigate whether household beliefs about different aspects of the macro economy are influenced by socioeconomic status measures by estimating the linear regression models in Table 3.3. Dependent variables in the models in the table are measures of macroeconomic expectations: the aggregate optimism measure *OPTINDEX* in the first column, and its separate components in the following five columns. Independent variables include the person’s income rank as a quintile (defined with respect to the person’s year-age group), an indicator for whether the person has a college degree or higher education, and interactions of an NBER recession indicator with the two SES measures. All the regressions in the paper also include fixed effects for the year-month of the survey, as well as indicators for the respondents’ age, gender, and marital status. The standard errors are clustered by time, specifically by year-month.

As shown by the results in Table 3.3, people’s SES characteristics are significant predictors of their beliefs regarding future macroeconomic conditions (*PSTK*, *BUS12*,

BUS5, *BEXP*, *UNEMP*), as well as of their aggregate optimism index *OPTINDX*.

For each of our five measures of beliefs, we find that having a higher income rank among people in the same age category and in the same year, and having a college or higher education are significant predictors of the level of optimism in the respondents' expectations. When the dependent variable captures expectations about future stock market returns (*PSTK*), we find that during non-recession months, for each increase of one quintile in respondents' income rank, the probability they estimate for the U.S. stock market to have a positive return over the next year increases by 3.2%. People with at least a college degree, on average believe that the probability of positive stock market return is 7.4% higher than people without a college education.

Similarly, we find that during non-recession months, those with better SES provide significantly more optimistic expectations for *BUS12*, *BUS5*, *BEXP*, *UNEMP* and have higher values for the overall belief measure *OPTINDX*. For example, an increase of a person's income rank by one quintile leads to an average increase of 0.063 in *OPTINDX*, which is about a tenth of the standard deviation of this variable. Having a college degree has a similar effect, as it leads to an increase in *OPTINDX* of 0.069. All of these effects are statistically significant at $p < 0.05$ or better.

A possible concern regarding the finding that lower income individuals have more pessimistic macroeconomic expectations is that the effect is driven by a lack of financial literacy, which might induce low income people to be more confused, in a pessimistic manner, about the macroeconomy. To address this concern, in unreported analyses we estimate similar models as in Table 3.3, but only for people with a college degree, and we continue to find a significant and positive effect (0.051, $p < 0.01$) of *IncomeRank* on people's aggregate expectations as measured by *OPTINDX*. This effect is similar in magnitude to that estimated in the specification in the first column in Table 3.3 (i.e.,

0.063). In other words, even among those with high education, we find that individuals earning more money are more optimistic about future macroeconomic developments than their lower-income peers.

While during normal economic times higher-income and higher-education individuals are more optimistic about macroeconomic developments, the coefficient estimates in Table 3.3 on the interaction terms of the NBER recession indicator and either SES measure show that, consistent with the patterns in Figures 3.1 and 3.2, the SES-related wedge in expectations is significantly smaller during recessions. In the case of education, the effect of a college degree on OPTINDX is two thirds smaller during recessions (instead of 0.069, it is 0.069-0.047, or 0.022), and the effect of income rank is a third smaller (instead of 0.063 it is 0.063-0.02, or 0.043). These estimates are significant at $p < 0.01$ or better.

Our analysis so far has documented two broad empirical patterns: first, lower SES people hold more pessimistic macroeconomic beliefs, and second, during recessions the difference in macroeconomic beliefs of those with high and low SES diminishes considerably. The fact that the gap in expectations between households from different SES levels is not constant over time is not surprising. Households from high and low SES levels may differ in the economic shocks they experience, the information they receive, and the way they process information. Building on this intuition, in the next section we investigate a potential mechanism that may be driving our main results.

3.3.2 Mechanism: Extrapolation from personal circumstance

It is possible that individuals form beliefs about aggregate macroeconomic conditions by extrapolating from their own economic situation. This idea is similar to the "local thinking" concept proposed by *Gennaioli and Shleifer (2010)*. In their model, an

agent combines data received from the external world with information retrieved from memory to evaluate a hypothesis, with limited and selected recall of information. In our context, local thinking would mean that when asked about macroeconomic conditions, people can only envision a limited number of scenarios, and those that do come to mind are more representative, or stereotypical, for these individuals. Therefore, people would forecast macroeconomic conditions more similar to their own personal situation than they ought to be, given objective information about the economy in general. Moreover, as long as the scenarios that come to mind more likely are more recent, this would suggest that recent changes in one's personal economic situation would be particularly salient in the formation of macroeconomic expectations.

This mechanism can account for the first main fact we document, namely, that households with better incomes or education have more optimistic beliefs about macroeconomic outcomes such as stock market returns or unemployment levels. The second fact we document, namely the convergence in beliefs across SES levels during recessions, is also a consequence of this mechanism if during recessions higher SES households suffer, or perceive to suffer, a larger decline in their economic wellbeing in general.

There is suggestive evidence that higher SES people indeed have more cyclical income, consumption growth, or wealth, and thus face more cyclicity in their economic situation. *Parker and Vissing-Jorgensen* (2010) analyze the sensitivity of household income to aggregate income, where household income includes wages, as well as transfers (which impact incomes for low SES people) and realized capital gains (which impact incomes for higher SES people). Their analysis documents that the people with the least cyclical income are those in the lowest income quintile, and the people with the most cyclical income are those in the highest income quintile.⁵ *Saez* (2015) finds that

⁵When income is measured solely with W-2 based wages, and does not include transfers or realized

the taxpayers in the top percentile of the income distribution experienced much sharper falls in income during the 2001 recession and the Great Recession than other taxpayers. The sensitivity of consumption growth to aggregate consumption growth is much greater for people in the top quintile of income, relative to those in the bottom four quintiles (*Parker and Vissing-Jorgensen (2009)*). Luxury good consumption—which is, presumably, an indication of the financial well-being of wealthier households—is more highly correlated with stock market returns than other consumption categories (*Ait-Sahalia et al. (2004)*). The fraction of net wealth invested in equity is significantly greater for people in the top two quintiles of wealth relative to those in lower wealth quintiles (*Gomez (2017)*), implying that the wealth of higher SES people is more exposed to market conditions, in line with the finding in *Bosworth (2012)* that the most pronounced drop in wealth during the 2007-2009 was among households in the top third of the distribution in terms of either income or wealth as of 2007.

Below, we provide evidence from the Michigan survey that in terms of subjective perception but also objective measures, higher income and higher education individuals experience a more pronounced decline in their economic situation during the recessions in our sample. Moreover we show that these changes in people’s personal economic situation are factors that drive expectations about future macroeconomic conditions, and the SES-wedge in these expectations documented earlier in the analysis.

Our first measure of the recent change in a person’s economic circumstances is given by the subjective assessment as to whether the individual is worse off, the same, or better off in terms of their finances, relative to a year before the survey. Figure 3.3 shows that in recessions high SES individuals become more likely to report that their personal economic situation is worse than a year before, relative to non-recession times,

capital gains, then the sensitivity of wage income to GDP is U-shaped: it is high for low income and for high income groups. See *Guvenen et al. (2014)* and *Guvenen et al. (2017)*.

and the worsening of personal economic circumstance is more pronounced for high SES relative to low SES individuals.

The regression models in the first two columns in Table 3.4 document similar results as those in Figure 3.3. In non-recession times, people are 5.7% ($p < 0.01$) less likely to report that their personal finances are worse than a year before, if their income rank increases by one quintile. Similarly, in non-recession times, people with a college degree are 2.5% ($p < 0.01$) less likely, relative to those without a college degree to report that their personal finances have worsened since a year before. During recession months, however, these gaps in the likelihoods of people of high versus low SES to report a change for the worse in their economic situation become about a fifth smaller, as can be seen by adding the non-recession coefficients to those on the NBER recession interaction terms. A similar effect is observed when instead of using the simple *Worse off* indicator, we use the *1-yr Change in Personal Situation* measure, which can take the values -1, 0 or 1 to indicate whether people feel their finances have gotten worse, stayed the same, or improved in the past year. We find that this variable is more positive for higher SES individuals during non-recession times, but the gap between high and low SES people in their reports regarding the change in their finances narrows by about a fifth during recession months.

Our second measure of the recent change in a person's economic situation is given by the individual's report about the type of business-related news that are salient to them at the time of the survey. Each person is asked whether they have followed the news recently, and if so, they are asked to list up to two different pieces of news, which are later coded by the interviewer as being good news or bad news. Here, for each respondent we create a variable (*Amount of good news*) equal to 0, 1, or 2, depending on how many pieces of positive economic news they mentioned to the interviewer. The

average of this variable in the sample is 0.34.

We find that during non-recessionary times, higher SES individuals report hearing more news of a positive nature relative lower SES people, as can be seen in Figure 3.4, but this SES-related gap in good news salience disappears during recessions. The regression model in column three in Table 3.4 documents similar results as those in Figure 3.4. During non-recession months, the amount of good news reported is 0.045 ($p < 0.01$) higher for each increase of a quintile in the income rank of a person, and 0.157 ($p < 0.01$) higher in the case of college degree holder versus those with a lower education. These differences across SES levels in the amount of good news salient to people drops during recession months, by about a half.

In unreported results, we also show that higher SES individuals are more likely to be aware of economic news than lower SES individuals, especially during normal economic times. To the extent that people in different SES categories have different stakes when it comes to following economic developments, this evidence is in line with rational inattention theory (*Sims (2008), Kezdi and Willis (2011)*), which states that individuals with high stakes have strong incentives to pay more attention to macroeconomic signals, and thus they will update their macroeconomic beliefs frequently. The opposite is true for individuals with low stakes, who will engage in infrequent updating and thus will exhibit sticky expectations. Examining whether people report hearing any business news at all, irrespective of their type, we document a pattern very much in line with the pro-cyclical inattention results in *Coibion and Gorodnichenko (2015)*, namely, we see that across all SES levels, people are less aware of business news during good economic times.

As our final measure of changes in a person's economic environment, we use county level information about unemployment rates, provided by the Bureau of Labor Statis-

tics with a monthly frequency, thus matching the frequency of the expectations data. In column four in Table 3.4 we examine whether there is a change, driven by the occurrence of recessions, in the wedge between economic conditions in the communities where higher SES individuals live relative to those where lower SES individuals reside. We were able to have county-level information from the Bureau of Labor Statistics merged in with the publicly available data from the Michigan Survey, for the 2000-2014 period.⁶ Specifically, as our measure of economic conditions in the county of the respondent we use unemployment growth over the three months prior to the month when the individual is in the survey. We find that during non-recession months, unemployment growth in respondents' communities is similar across high and low income or education individuals. The average during the sample for the three-month growth in the county unemployment rate is about 1.2%. However, unemployment growth is higher during recessions in the counties of residence of higher SES individuals. A change from one quintile to the next higher quintile in terms of a person's income corresponds to an increase of 0.2% ($p < 0.05$) in the three-month growth in unemployment observed in the person's community. For an increase in education, from having no college degree to having one, the corresponding increase in the three-month growth in the unemployment rate in the person's county is 0.5% ($p = 0.1$). These are sizeable effects, given the mean of this growth, namely, 1.2%. This suggests that higher SES people may observe a faster decline in the economic situation of their community during recessions, relative to lower SES individuals.

The two panels in Figure 3.5 present residual plots for the optimism index, split by SES, during 1980-2014. SES is defined based on income in the top panel, and education in the bottom panel. The residual optimism shown in the figure is obtained after

⁶This merge can not be done for times prior to year 2000 due to the lack of county identifiers in the MSC data up to that year.

controlling for measures of personal circumstance, specifically respondents' assessment whether their own personal finances have improved in the past year, and the amount of good business news heard recently. As can be seen by comparing Figure 3.5 and Figure 3.1, the SES-related differences in beliefs diminish significantly, when beliefs are measured by this residual optimism index.

This result can also be seen in the regressions in Table 3.5. Once we control for changes in a person's own economic situation, the amount of good news salient to them, and for the county economic condition as measured by unemployment (for the subsample for which we have this data), the coefficients on the SES variables – income rank and education – and their interactions with the NBER recession indicator drop in magnitude significantly, by roughly a half. This indicates that indeed the SES-related wedge in expectations documented in the paper, and its pro-cyclical nature, can be explained at least in part by people extrapolating from local, personal changes in economic conditions.

3.3.3 Importance of SES-driven expectations for household choices

The results so far indicate that a person's socioeconomic situation shapes their beliefs about future macro-level economic conditions, such that higher SES individuals hold more optimistic beliefs about future stock returns, unemployment and business conditions. In the next step of the analysis, our goal is to quantify the impact of SES, specifically through its influence on beliefs, on households' economic choices.

It is natural to expect that aspects of a person's SES will have a direct effect on that person's economic choices. For example, higher income individuals or those who are better educated likely have easier ways to invest in stocks relative to lower income individuals, perhaps because of access to retirement accounts at work, or simply

because they have money left to save after paying their bills each month. Similarly, higher SES individuals are less likely to face financial constraints and thus more likely to consider purchasing homes, cars or durable goods.

Therefore, the total effect of SES on household choices comes from two sources: (1) the direct effect of SES on these choices – for example, because higher income leads to easier access to retirement accounts, and (2) the indirect effect of SES on these choices through the belief channel – for example, because higher SES individuals hold more optimistic beliefs about the distribution of stock returns, or other macroeconomic developments.

We can measure the relative importance of the direct and indirect effects of SES on people’s economic choices using the analysis in Table 3.6. The dependent variables in the models estimated in the table capture the respondent’s investments in stocks (*Invest* and *InvestShare*) and their propensity to assess when completing the survey that it was a good time to purchase homes, durables or cars (*HOM*, *DUR*, *CAR*). The independent variables include our two SES dimensions (income rank and education), as well as the person’s aggregate belief about future macroeconomic conditions (*OPTINDX*).

The direct effects of the two SES measures on household choices are given by the estimated regression coefficients in the models in Table 3.6 for each of the two measures. As expected, we find that higher SES people are more likely to participate in the stock market, invest more money relative to their income in equities, and are more likely to believe that it is a good time to purchase homes, cars or durable goods. For example, the regression in the second column in Table 3.6 shows that an income rank higher by one quintile corresponds to 14.2% ($p < 0.01$) increase in the probability that the person invests in stocks. This is a large effect, considering that in our data, as shown

in the summary statistics in Table 3.2, 65% of respondents invest in the stock market. Individuals with a college or higher education have a 12% ($p < 0.01$) higher probability of investing in stocks, compared to those less educated. Similarly, the results in the third column in Table 3.6 show that people with higher incomes and a college or higher education, conditional on investing in equities, have a higher amount of money, expressed as a fraction of their annual income, invested in stocks.

The regression models in the last three columns in Table 3.6 show that, in general, both dimensions of SES are significant and positive predictors of people's assessment that it is a good time to purchase a home, or a car or durable goods. For example, having a college or higher education translates into an improvement of 0.08 ($p < 0.01$) in the person's attitude towards buying a home, which is sizeable, given that the mean of this variable is 0.44 in our sample. The effect of increasing one's income rank by one quintile on the attitude towards buying a home is similar in magnitude (0.071, $p < 0.01$) to that of having a college education. When the dependent variable captures the attitude towards buying durables, or cars, the estimated direct effects of the SES dimensions are in line with those observed when the dependent variable refers to people's home buying attitude. The only exception is that college educated people are not significantly different than those without a college degree to indicate that it is a good time to purchase durables.

Since in the regression models in Table 3.6 we control for the person's beliefs about future macroeconomic conditions, as measured by their overall optimism, *OPTINDEX*, the above effects of SES on the person's decisions regarding investments and purchases represent the direct effects of SES on these decisions, aside from any indirect effects of SES through the belief channel.

To measure the indirect effects of SES, and the relative importance of the direct

versus the indirect effects, we follow standard methodology used in mediation analysis. The results are presented in presented in Table 3.7, and show that SES changes household choices through both the direct channel and the indirect, belief-related, channel.

For example, looking at the decision to invest or not in stocks (first row in Table 3.7), the direct effect of an increase of one quintile in a person's income rank is an increase of 14.2% in the probability of investing, as shown earlier in the regression analysis in Table 3.6. The indirect effect of the same increase in the income rank, through the belief channel, is equal to the product of two quantities: the coefficient estimate on *Income Rank* in the regression model predicting the belief *OPTINDEX* in the first column of Table 3.6, and the coefficient estimate on *OPTINDEX* in the regression model from Table 3.6 that predicts the *Invest* variable. Thus, the indirect effect is $0.06 \times 0.035 = 0.2\%$. The total effect of an increase of one quintile in income rank on the probability of investing in stocks is the sum of the direct (14.2%) and indirect (0.2%) effects, namely 14.4%. The importance of the indirect, belief-related channel, is given by the ratio of the indirect to total effect, which is equal to 1.5%. In other words, a person's income rank is a positive predictor of the decision to invest in stocks, and about 1.5% of the positive effect of income on the probability to invest is attributable to the beliefs that the person holds about future macroeconomic conditions. The rest of the effect is attributable to other income-related factors that are not about differences in beliefs.

The importance of the indirect, belief-channel is higher for other SES measures and household decisions. For example, analyzing the decision to invest in stocks, the indirect channel accounts for 1.8% of the positive effect of a college education. When analyzing the share of income invested in stocks, the indirect, belief-related channel, accounts for 8.83% of the positive effect of higher income rank, and 2.45% of the

positive effect of a college education. When analyzing people's home buying attitude, the indirect, belief-related channel, accounts for 14.57% of the positive effect of higher income rank, and 13.58% of the positive effect of a college education. The indirect, belief-related channel accounts for 24.67% of the positive effect of higher income rank on attitudes towards durables purchases, and for 18.7% of the positive effects of either higher income rank, or higher education, on attitudes towards car purchases. Thus, the effects of SES on household choices and attitudes are in part driven by the differences in macroeconomic expectations of people with different SES.⁷

So far in the analysis we have related several decisions of individuals to their aggregate belief about future economic conditions, *OPTINDX*. We will now turn towards analyzing a specific aspect of these beliefs, namely, the subjective probability that the U.S. stock market return will be positive over the next year (*PSTK*), to understand how it relates to the respondents' decision regarding making investments in stocks.

While SES-related variables such as income and participation costs impact whether a household invests in the stock market (e.g., *Vissing-Jorgensen (2002)*), our results so far suggest that SES-driven variation in beliefs about stock returns may also explain the variation across SES levels in terms of the decision to invest, and the fraction of income invested in stocks. We thus investigate the relative importance of the SES-related stock market belief channel, relative to that of other SES-related factors, on stock investment decisions.

The results in Table 3.8 indicate that SES measures, as well as *PSTK*, are positive predictors of a person's decision to invest in equities, and conditional on investing, of the share of income invested in stocks. The relative importance of the direct effect

⁷An additional way to quantify the role of the SES-induced beliefs on household economic choices is to examine the contribution of these beliefs to the standard deviation of households' choices. In unreported analyses, we find that this alternate approach leads to similar results as documented here.

of SES measures, and their indirect effect through expectations, is illustrated in the results in Table 3.9.

As expected, the results in Table 3.8 show that, controlling for the belief about stock market returns, our SES measures are positive and significant predictors of both the invest decision, as well as of the share of income invested in stocks. In other words, income rank, and education directly influence a household's stock market investment decisions. However, as our analysis in Table 3.3, and in the first column in Table 3.8 shows, these SES measures also impact *PSTK*, the belief about whether the stock market return will be positive over the next year, which by itself, as seen in Table 3.8, influences the households' decision whether, and how much, to invest in stocks.⁸

The coefficient estimates in Table 3.8 allow us to estimate the direct and indirect (via the belief channel) effects of each of the SES measures on stock market investment decisions. Specifically, increasing a person's income rank by one quintile increases the probability of stock market participation by 13.4%, and the share of income invested by 7.3%. The indirect effects of income rank on these two outcomes, through the belief channel, are obtained by multiplying the coefficient estimates on *PSTK* in the first column in Table 3.8 and those in the second, and third column, respectively. Namely, the indirect effects of increasing the income rank by one quintile on the probability of participation and on the share of income invested in stocks are increases of 0.5% (i.e., 0.031×0.176) and 1.5% (i.e., 0.031×0.491), respectively. Thus the total effects of increasing one's income rank by one quintile are an increase of 13.9% (i.e., $13.4\% +$

⁸A possible concern is that there is a mechanical correlation between the expectations expressed by survey respondents and their declared choices, stemming from people's desire to look "consistent" in their survey answers. Specifically, an individual who declared that he does not invest in the stock market may later express pessimistic expectations about future stock market returns, to justify to himself and the experimenter why he holds no equities. Fortunately, the survey design used by the MSC staff alleviates this concern, because people are first asked to estimate the probability that the stock market will have a positive return, and only later are asked to calculate how much money, if any, they invest in stocks.

0.5%) in the probability of participation in the stock market, and an increase of 8.9% (i.e., 7.3% + 1.5%) in the share of income invested. The indirect effect of higher income, though inducing more optimistic beliefs about the stock market, represents 3.93% of the total effect of income on the participation decision (i.e., 0.5%/13.9%), and 17.21% of its total effect on the share of income invested in stocks (i.e., 1.5%/8.9%).

When examining the effects of education on the decision to invest in stocks and on the share of income invested, we also find sizeable indirect effects of this SES measure on the two decisions. Specifically, following the same procedure described earlier for quantifying the direct and indirect effects of income rank on stock investment decisions, we find that having a college degree increases the probability of investing in stocks by 11.7% and 10.84% of this total effect of education on participation is coming from the indirect, belief-related channel. Also, having a college or better education increases the share of income invested in stocks by 32.4% and the fraction of this total effect that is driven by the belief channel is 10.92%. These results are summarized in Table 3.9.

Thus, we find that people who have higher incomes and are more educated are more likely to invest in stocks, and are willing to invest more of their income in these assets, and this is in part because they hold more optimistic beliefs about the stock market return distribution.

When studying the effect of one dimension of expectations, namely, *PSTK*, on investment decisions, rather than using an aggregate measure based on several macroeconomic beliefs, such as *OPTINDX*, it is important to alleviate the concern that there may be substantial measurement error in the *PSTK* variable. To do so, in additional analyses presented in the Supplementary results, we have used an instrumental variables estimation strategy, based on the idea that the several other reported macro belief variables in the Michigan Survey (i.e., *BUS12*, *BUS5*, *BEXP* and *UNEMP*) can be

used as instruments for *PSTK*, assuming their measurement errors are uncorrelated with the measurement error in *PSTK*. We find similar effects either using the OLS or the IV approach, and thus in the paper we focus on the OLS results.

3.4 Caveats and limitations

Our interpretation of the results presented here is in line with the assertion in *Manski* (2004) and a large body of research using survey expectations that the subjective beliefs reported by respondents in the survey are independent of the respondents' preferences over outcomes. It is possible, though, that preferences lead survey respondents to tilt their expectations in a particular direction. For example, ambiguity aversion can be represented as a pessimistic tilt in subjective probabilities (*Hansen and Sargent* (2016)). If respondents perceive ambiguity about probability distributions, it is possible (although not necessarily true) that they report their pessimistically tilted probabilities in the survey. This interpretation is consistent with the fact that macroeconomic expectations in the Michigan Survey of Consumers are systematically too pessimistic relative to professional forecast or econometric model-based forecasts (*Bhandari et al.* (2016)). Viewed through the lens of these models, our findings indicate that individuals with lower SES have subjective beliefs that have a greater tilt towards pessimism and that that their tilt is less cyclical than the tilt of high-SES individuals.⁹

We also interpret the respondents' answers regarding household decisions – such as choices concerning investing in the stock market, or attitudes towards buying homes, cars and durable goods – as good proxies for these individuals' actual economic behavior. That being said, we do not have administrative data to verify these survey

⁹*Brunnermeier and Parker* (2005) provide an alternative model of optimistically-titled probabilities. A tilt towards optimism is, however, in conflict with the fact that expectations seem to be too pessimistic on average.

answers. However, there are two reasons to believe that people’s survey responses are truthful.

First, as shown earlier in our analysis, there is a clear relationship between a respondents’ expectations and their own household decisions as reported during the survey, which implies that the data on decisions can not be simply noise. This correlation between expectations and behavior is also found at the aggregate level, as shown for example in *Carroll et al.* (1994), who document that the degree of optimism in MSC expectations is a strong positive predictor of the change over the following year in the aggregate level of personal consumption, including purchases of cars, other goods, and services.

Second, the survey measures of household behavior are strong predictors of aggregate macroeconomic outcomes. For example, *Cai et al.* (2015) find that the MSC aggregate response regarding whether it is a good time to buy a home is a strong and positive predictor of the volume of transactions in the housing market measured over the following year. In additional analyses of our own we find that the MSC respondents’ monthly aggregate attitude *DUR* regarding purchasing durables is highly correlated ($\rho=0.5$, $p < 0.01$) with the aggregate contemporaneous monthly demand for durable goods, obtained from the FRED database of the Federal Reserve Bank of St. Louis. Similarly, we find there there is a high correlation ($\rho=0.6$, $p < 0.01$) between the MSC aggregate monthly attitude *CAR* towards buying cars, and the contemporaneous total car sales reported in the FRED database.¹⁰

Therefore, while we can not verify for each respondent whether their household decisions are truthfully reported, at least we observe that in the aggregate, the reports

¹⁰The durable goods demand data and the total car sales data are available on the website of the Federal Reserve Bank of St. Louis at <https://fred.stlouisfed.org/series/DGORDER>, and <https://fred.stlouisfed.org/series/TOTALSA>, respectively. For our analysis we detrend these monthly time series to account for population growth.

of individuals in the MSC correspond to actual macroeconomic outcomes.

3.5 Conclusion

Using a sample of more than 170,000 responses from individuals recruited to participate in the Michigan Survey of Consumers each month from 1980 to 2014, we document that people’s socioeconomic status is a significant driver of the beliefs they hold about future macroeconomic conditions such as the performance of the stock market and changes in unemployment or business conditions in general, and this in turn has significant effects on people’s economic choices. Specifically, we find that higher SES individuals – namely, those with higher income and higher education – are more optimistic about future macroeconomic conditions during non-recessionary times, and these optimistic beliefs are in part responsible for these households’ higher propensity to invest in stocks or to be inclined to purchase homes, cars or durable goods. Importantly, the SES effect on beliefs is pro-cyclical, as we find that during recessions, the wedge in expectations across SES levels diminishes significantly. We provide evidence that suggests that extrapolation from personal experience is a likely mechanism for the observed differences in expectations of people with different socioeconomic standing, as well as for the convergence of these expectations during recessions.

Our findings suggest that differences in macroeconomic expectations across people with different socioeconomic standing may lead to an increase in wealth inequality in the population over time, since these expectations influence household decisions such as investing in stocks or in real estate. However, our results also point to the possibility that due to the convergence in expectations that occurs during recessions, wealth inequality may diminish during those times. An interesting avenue for future

work is to quantify the importance of divergence in expectations across SES strata for the dynamics of the wealth distribution in the population.

Figure 3.1: Macroeconomic optimism during 1980-2014, by SES level. Monthly level data. Income quintiles are created within year-age groups. Shaded areas represent NBER recession periods.

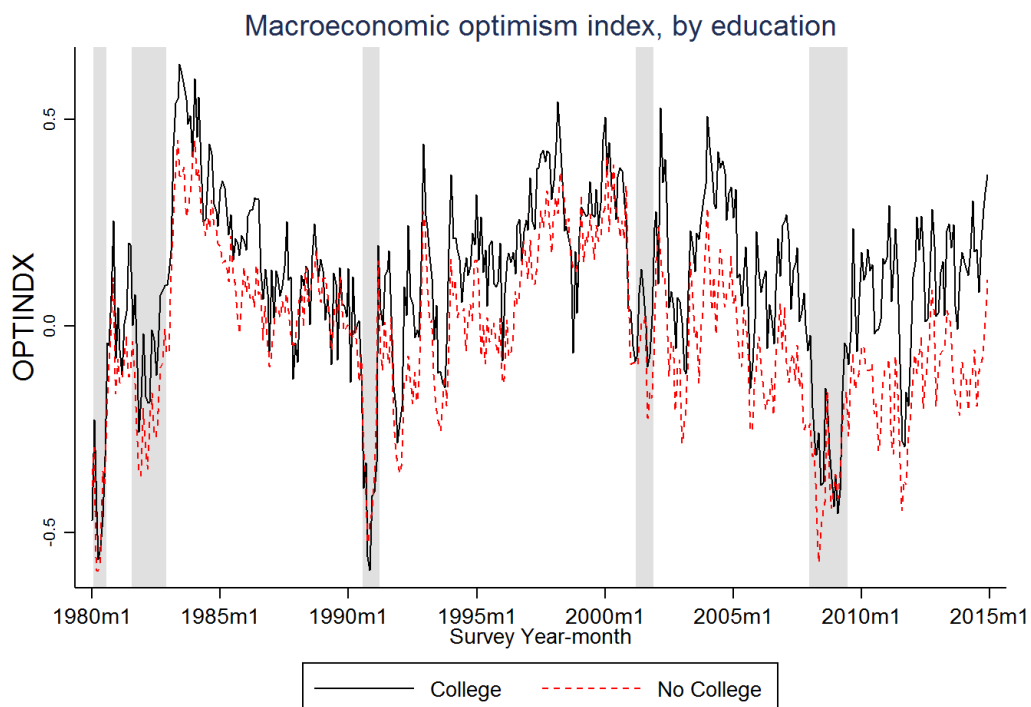
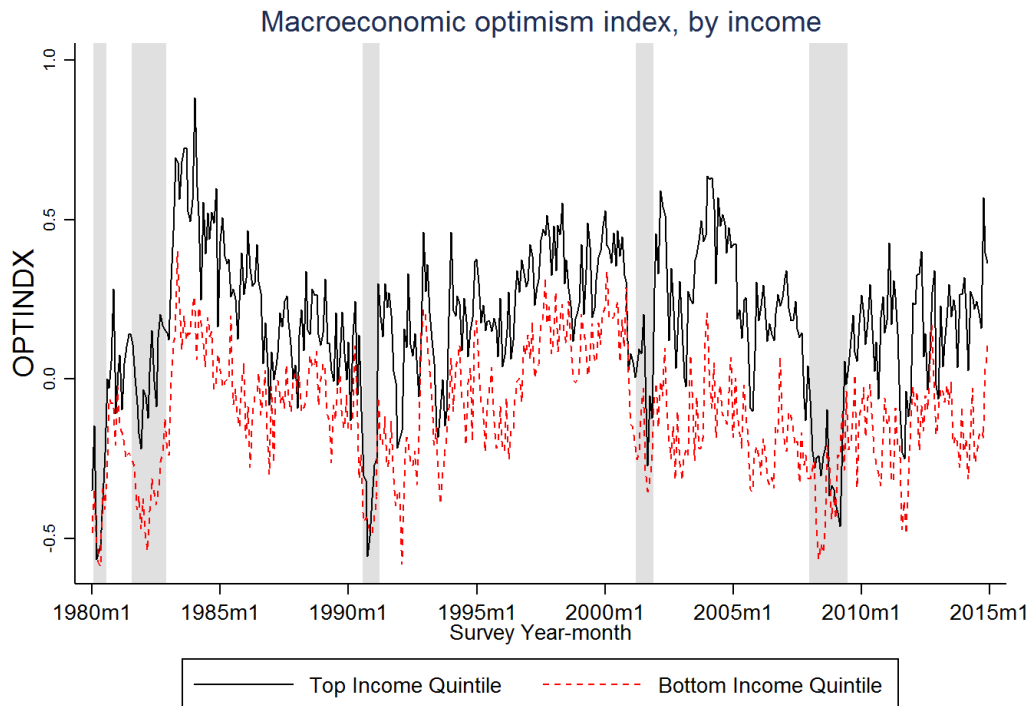


Figure 3.2: Stock market expectations during 2002-2014, by SES level. Expectations refer to individuals' stated probability that the US stock market would have a positive return over the following 12 months. Monthly level data. Income quintiles are created within year-age groups. Shaded areas represent NBER recession periods.

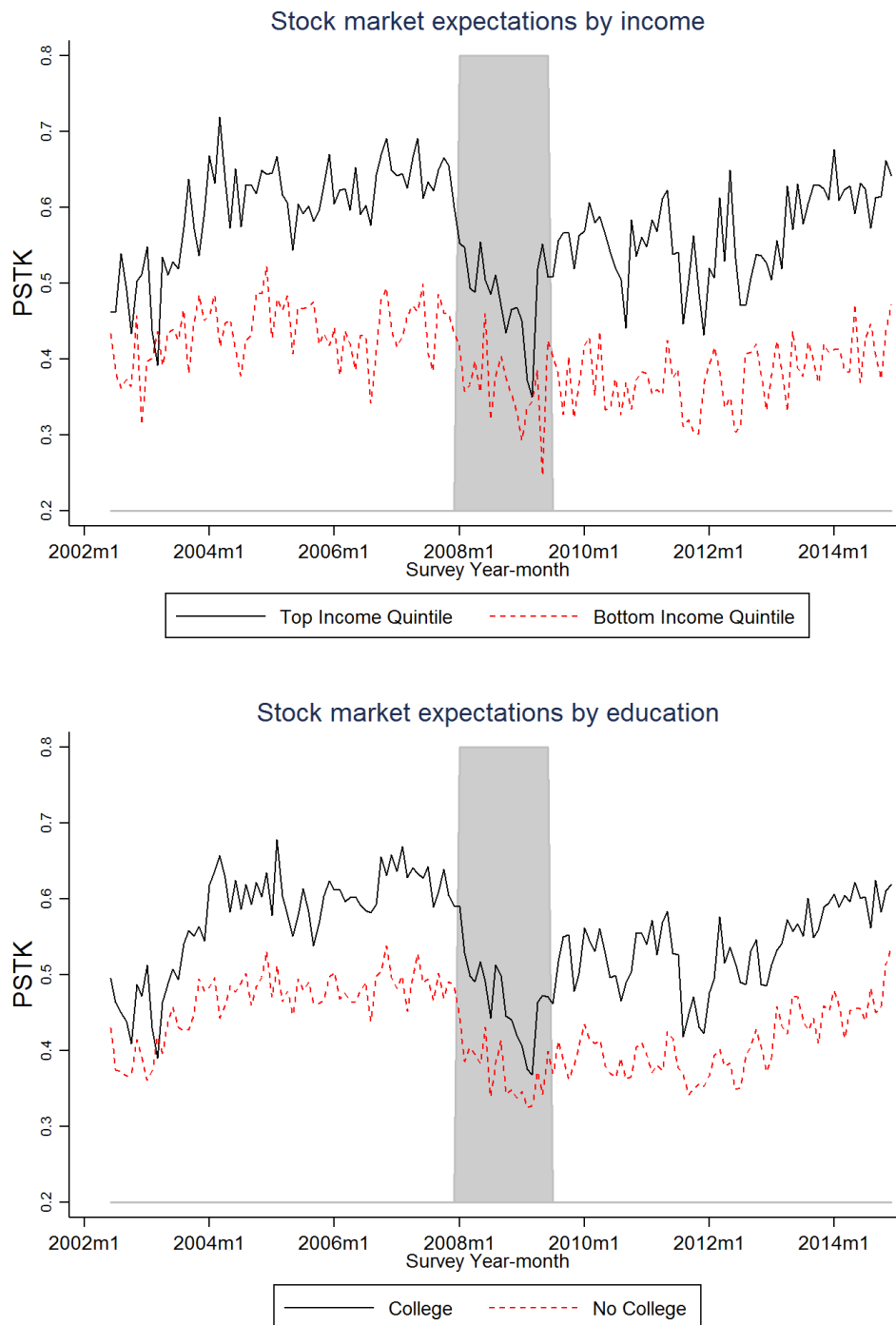


Figure 3.3: Fraction of population reporting that their own personal economic situation is worse relative to one year before, by SES level.

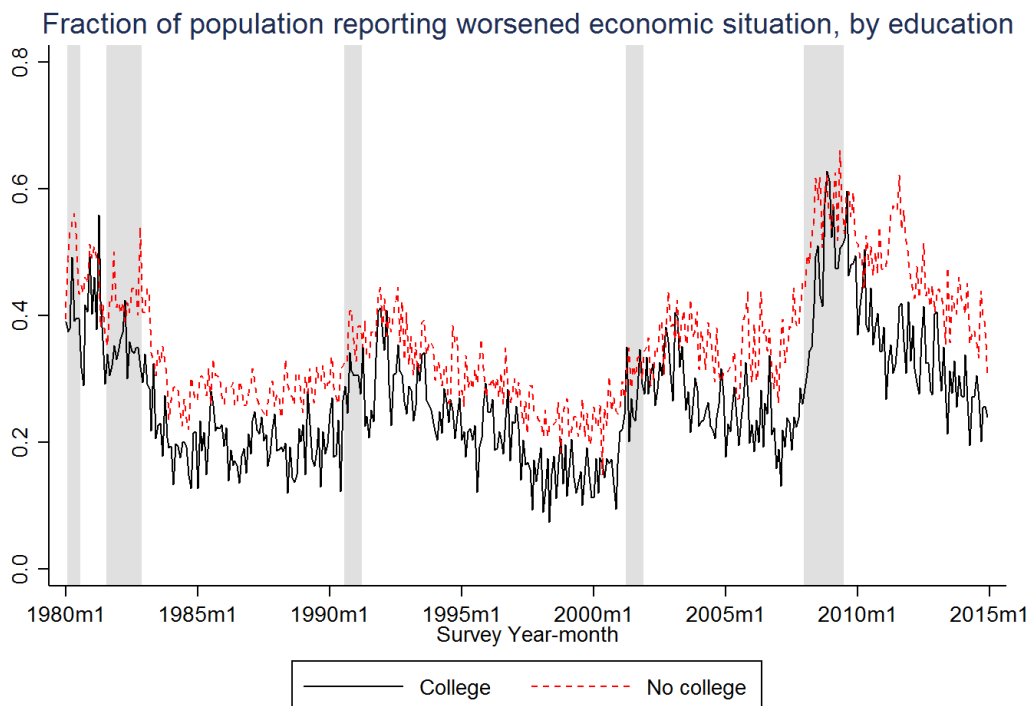
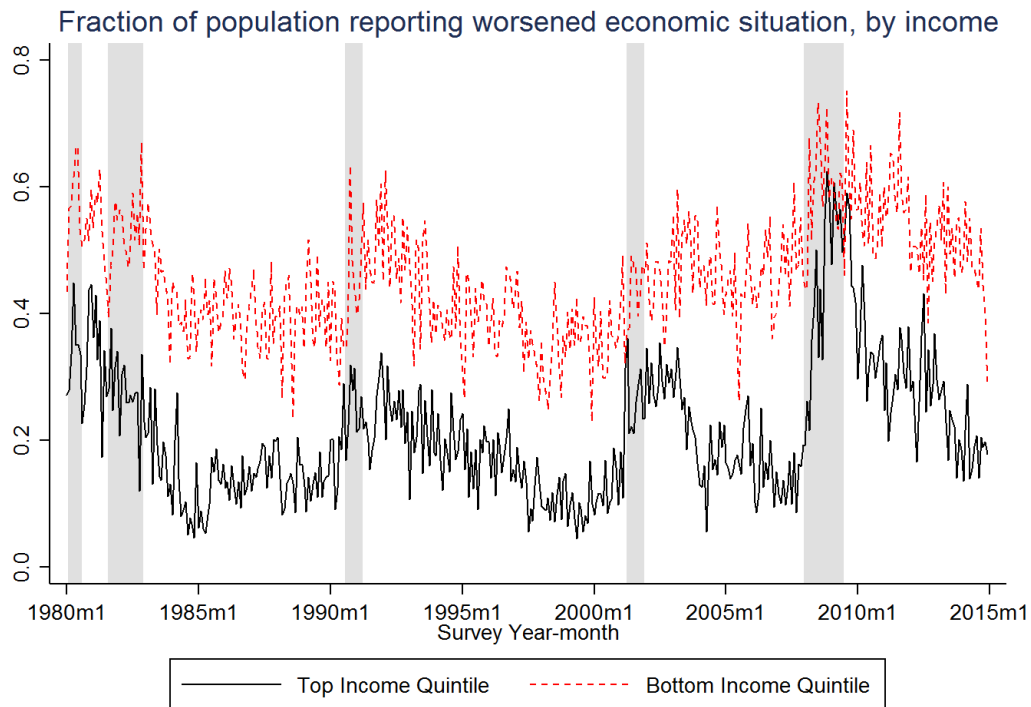


Figure 3.4: Amount of good news heard, by SES level. Possible values for each individual are 0, 1, or 2, depending on how many pieces of good economic news they said they heard recently.

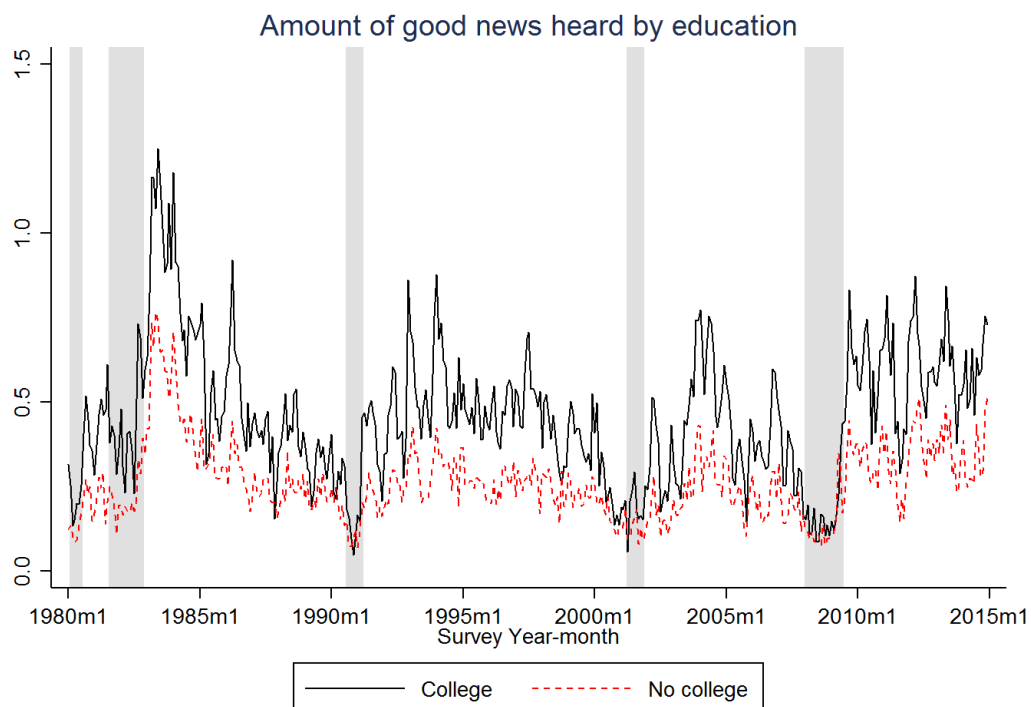
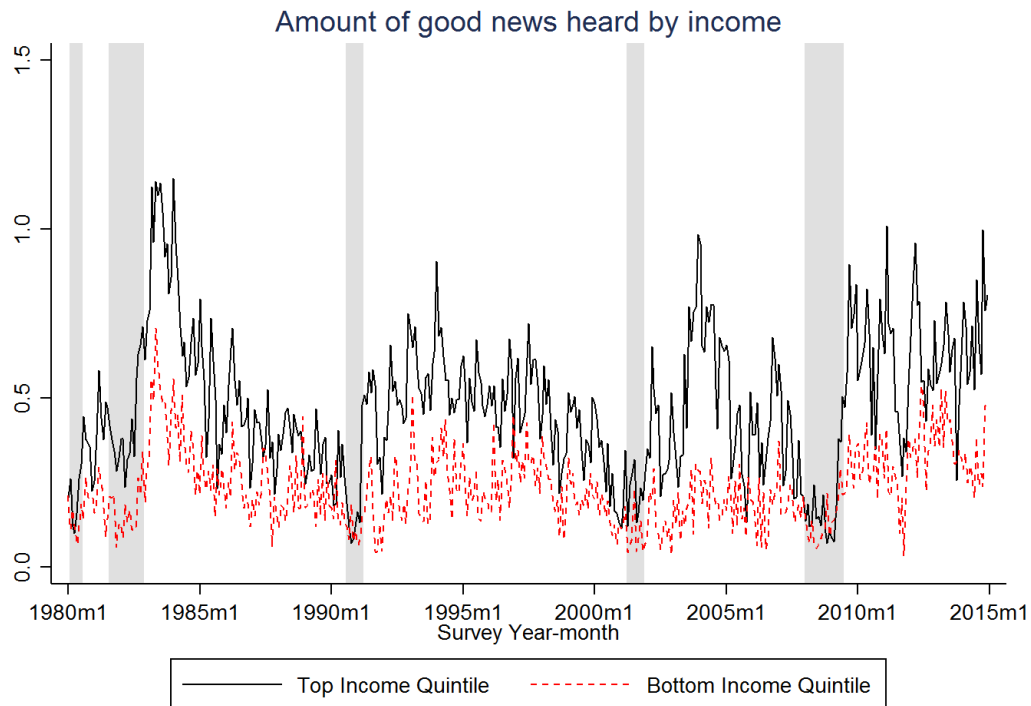


Figure 3.5: Residual of the optimism index obtained after controlling for the respondents' perceived change in their own economic situation over the past year, and the amount of good news heard, shown by income levels (top panel) and education levels (bottom panel).

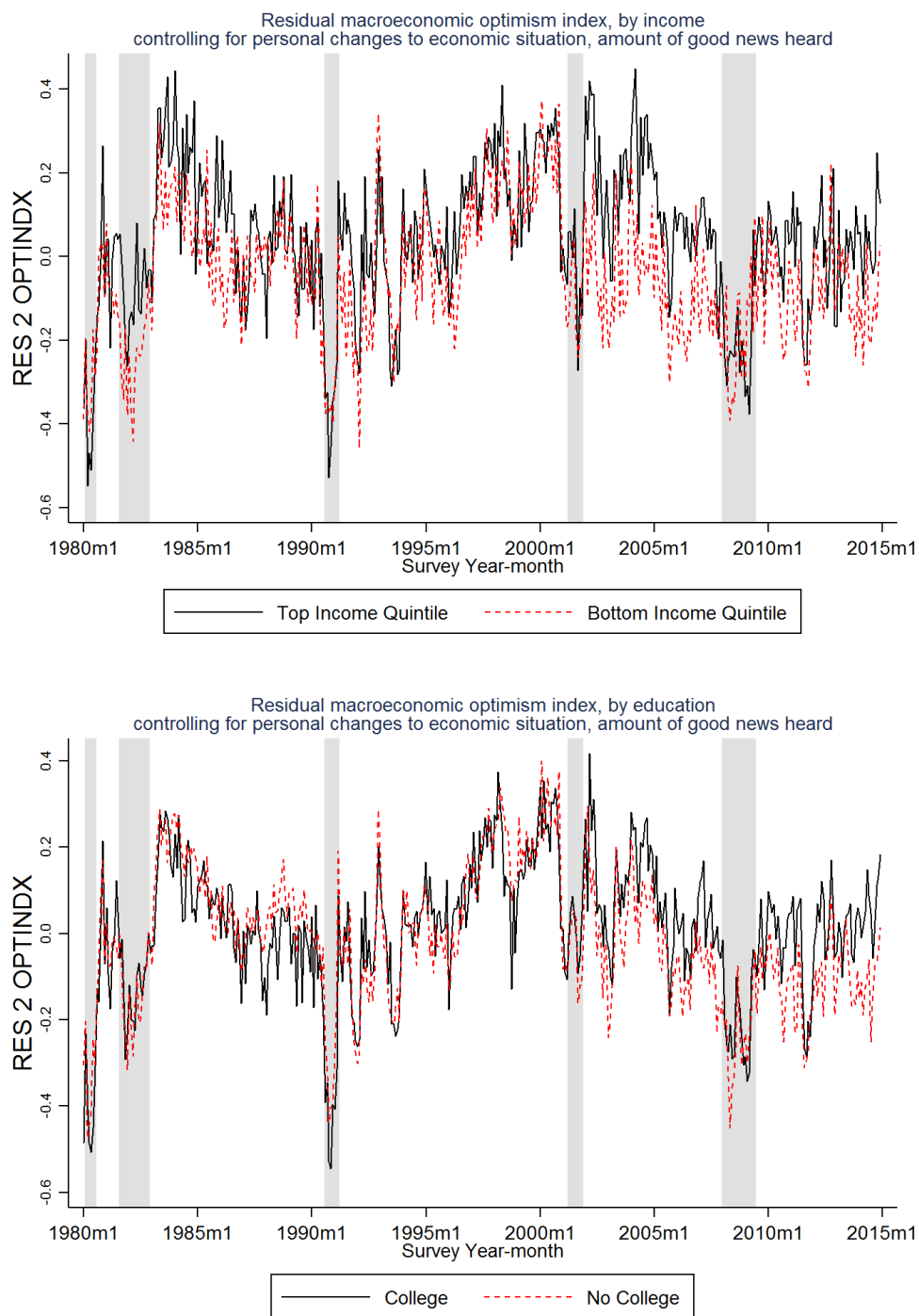


Table 3.1: Data Definition

Variable	Description	Source	Values
PSTK	Percent Chance of Invest In-crease 1 Year	% Chance of investment in-crease in 1 year: What do you think is the percent chance that a one thousand dollar investment in a diver-sified stock mutual fund will increase in value in the year ahead, so that it is worth more than one thousand dol-lars one year from now?	0 - 100%. Only available during 2002-2014.
BEXP	Economy Bet-ter/Worse Next Year	And how about a year from now, do you expect that in the country as a whole busi-ness conditions will be bet-ter, or worse than they are at present, or just about the same?	Better a year from now About the same Worse a year from now
BUS12	Economy Good/Bad Next 12 Months	Now turning to business conditions in the country as a whole—do you think that during the next 12 months we’ll have good times finan-cially, or bad times, or what?	Good times Good with quali-fications Pro-con Bad with qualifi-cations Bad times
BUS5	Economy Good/Bad Next 5 Years	Looking ahead, which would you say is more likely – that in the country as a whole we’ll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depres-sion, or what?	Good times Good with quali-fications Pro-con Bad with qualifi-cations Bad times

Continued on next page...

... table 3.1 continued

Variable	Description	Source	Values
UNEMP	Unemployment More/Less Next Year	How about people out of work during the coming 12 months –do you think that there will be more unem- ployment than now, about the same, or less?	More unemploy- ment About the same Less unemploy- ment
1-Yr Change in Personal Finances	Personal Fi- nances Relative to A Year Ago	Would you say that you are better off or worse off finan- cially than you were a year ago?	Better now Same Worse now
Amount of good news	MSC Number of good news re- called	Do you recall news? De- scribe.	
County unem- ployment Invest	Bureau of Labor Statistics Invest in equities	County Unemployment, Monthly Do you have stock invest- ments?	Yes No
Invest Share	Overall amount invested in equi- ties, relative to current annual income	Defined as $\ln(\text{Amt In-}$ $\text{vested}/\text{Income})$, if Invest=1	
HOM	Home Buying Attitude	Generally speaking, do you think now is a good time or a bad time to buy a house?	Good Pro-Con Bad
DUR	Durables Buying Attitude	Generally speaking, do you think now is a good or a bad time for people to buy major household items?	Good Pro-Con Bad
CAR	Car Buying Atti- tude	Speaking now of the auto- mobile market –do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van, or sport utility vehicle?	Good Pro-Con Bad

Table 3.2: Summary Statistics. Expectations data are collected monthly during 1980-2014, with the exception of PSTK (stock market expectations), which is available only during 2002-2014.

	N	Mean	Median	StdDev	Min	Max
OPTINDX	171911	0.034	0.045	0.733	-1.540	1.771
PSTK	56821	0.483	0.500	0.293	0.000	1.000
BUS12	157332	0.014	0.000	0.965	-1.000	1.000
BUS5	162786	-0.060	-0.500	0.868	-1.000	1.000
BEXP	168954	0.096	0.000	0.691	-1.000	1.000
UNEMP	170579	-0.183	0.000	0.694	-1.000	1.000
Income Rank	171911	2.898	3.000	1.410	1.000	5.000
College Degree	171911	0.353	0.000	0.478	0.000	1.000
Worse off	171618	0.327	0.000	0.469	0.000	1.000
1-Yr Change in Personal Finances	171618	0.068	0.000	0.847	-1.000	1.000
Amount of good news	171014	0.339	0.000	0.619	0.000	2.000
County Unemployment Rate	68548	6.419	5.800	2.616	1.100	31.200
Invest	78825	0.622	1.000	0.485	0.000	1.000
Annual income (Real \$)	171911	71393	57429	63236	2	1041090
Amt Inv(Real \$)	43168	232604	80654	605282	985	14612452
Log(Amt Inv(Real \$))	43168	11.207	11.298	1.591	6.893	16.497
Log(Inv share)	43168	-0.157	-0.077	1.402	-5.565	5.085
HOM	169143	0.415	1.000	0.900	-1.000	1.000
DUR	163451	0.473	1.000	0.856	-1.000	1.000
CAR	163592	0.333	1.000	0.929	-1.000	1.000

Table 3.3: Macroeconomic expectations, socioeconomic status, and recessions. Linear regression models. Controls include dummies for year-month, age, gender, marital status. Higher beliefs indicate optimism. All Beliefs except PSTK and OPTINDX are categorical. OPTINDX : Overall macroeconomic optimism index; PSTK: Probability of stock market gain in next 1 year; BUS12: Financially good times in next 12 months; BUS5: Financially good times in next 5 years; BEXP: Overall business environment in next 1 year; UNEMP: Unemployment increase/decrease in next 1 year. Standard errors are clustered by year-month, and are robust to heteroskedasticity. T-statistics are shown in parentheses.

	OPTINDX	PSTK	BUS12	BUS5	BEXP	UNEMP
Income Rank	0.063 (31.41)	0.032 (27.67)	0.063 (22.55)	0.079 (33.28)	0.028 (14.54)	0.032 (16.45)
College Degree	0.069 (12.24)	0.074 (24.35)	0.035 (5.54)	0.088 (15.11)	0.027 (5.25)	0.035 (6.60)
Recession \times Income Rank	-0.020 (-3.40)	-0.011 (-2.92)	-0.049 (-7.24)	-0.016 (-2.71)	0.015 (2.46)	-0.027 (-4.45)
Recession \times College Degree	-0.047 (-3.85)	-0.016 (-2.35)	-0.082 (-5.47)	-0.025 (-1.72)	0.007 (0.52)	-0.060 (-5.19)
Observations	171549	56747	157013	162448	168607	170230
Adjusted R^2	0.104	0.113	0.132	0.075	0.043	0.069

Table 3.4: Changes to personal economic circumstances, SES and recessions. Linear regression models. Controls include dummies for year-month, age, gender, marital status. Standard errors are clustered by year-month, and are robust to heteroskedasticity. T-statistics are shown in parentheses.

	WORSE OFF	CHANGE IN PERSONAL SITUATION	AMOUNT OF GOOD NEWS	COUNTY UNEMPLOYMENT GROWTH
Income Rank	-0.057 (-50.96)	0.112 (53.56)	0.045 (24.75)	-0.000 (-1.18)
College Degree	-0.025 (-7.97)	0.063 (11.55)	0.157 (29.65)	-0.001 (-0.68)
Recession \times Income Rank	0.010 (2.82)	-0.024 (-3.99)	-0.022 (-5.79)	0.002 (2.14)
Recession \times College Degree	0.005 (0.53)	-0.010 (-0.61)	-0.095 (-6.61)	0.005 (1.66)
Observations	171371	171371	170772	68458
Adjusted R^2	0.077	0.113	0.091	0.258

Table 3.5: SES and expectations, controlling for changes to individuals' personal circumstances. Linear regression models. Controls include dummies for year-month, age, gender, marital status. OPTINDX : Overall macroeconomic optimism index. Standard errors are clustered by year-month, and are robust to heteroskedasticity. T-statistics are shown in parentheses.

	OPTINDX	OPTINX	OPTINDX 2000-2014	OPTINDX 2000-2014
Income Rank	0.063 (31.41)	0.034 (18.75)	0.070 (22.74)	0.035 (12.40)
College Degree	0.069 (12.24)	0.015 (2.95)	0.115 (14.15)	0.049 (6.62)
Recession \times Income Rank	-0.020 (-3.40)	-0.010 (-1.86)	-0.046 (-5.69)	-0.029 (-4.07)
Recession \times College Degree	-0.047 (-3.85)	-0.019 (-1.58)	-0.071 (-3.78)	-0.023 (-1.32)
1-yr Change in Personal Situation		0.146 (50.21)		0.157 (32.89)
Amount of Good News		0.292 (63.24)		0.360 (62.38)
County Unemployment				-0.007 (-4.99)
Observations	171549	170370	68450	68122
Adjusted R^2	0.104	0.191	0.101	0.225

Table 3.6: OLS Regressions of Choices and Attitudes on Beliefs and SES Variables. Controls include dummies for year-month, age, gender, marital status. Invest: Indicator for investment in equities; Invest Share: $\text{Log}(\text{Amt Invested}/\text{Income})$; HOM: Home buying Attitude; DUR: Durables Buying Attitude; CAR: Car Buying Attitude. Standard errors are clustered by year-month, and are robust to heteroskedasticity. T-statistics are shown in parentheses.

	OPTINDEX	Invest	Invest Share	HOM	DUR	CAR
Income Rank	0.060 (31.20)	0.142 (104.69)	0.075 (11.51)	0.071 (29.31)	0.037 (18.09)	0.061 (27.24)
College Degree	0.063 (12.22)	0.120 (35.20)	0.301 (23.47)	0.080 (15.15)	-0.007 (-1.32)	0.063 (11.09)
OPTINDEX		0.035 (15.08)	0.121 (12.68)	0.201 (47.40)	0.203 (45.64)	0.232 (51.47)
Observations	171549	78706	43139	168796	163120	163267
Adjusted R^2	0.104	0.284	0.238	0.196	0.102	0.093

Table 3.7: SES effects on choices and attitudes, direct and indirect through macroeconomic expectations.

Model	Direct	Indirect	Total	Indirect/Total (%)
Invest: Income	0.142	0.002	0.144	1.5%
Invest: Education	0.120	0.002	0.122	1.8%
Invest Share: Income	0.075	0.007	0.082	8.83%
Invest Share: Education	0.301	0.008	0.309	2.45%
Home: Income	0.071	0.012	0.083	14.57%
Home: Education	0.080	0.013	0.093	13.58%
Durables: Income	0.037	0.012	0.049	24.67%
Durables: Education	0	0.013	0.006	100%
Car: Income	0.061	0.014	0.075	18.66%
Car: Education	0.063	0.015	0.078	18.68%

Table 3.8: OLS Regressions of Investment Decisions on Stock Market Beliefs and SES Variables. Controls include dummies for year-month, age, gender, marital status. Invest: Indicator for investment in equities; Invest Share: $\text{Log}(\text{Amt Invested}/\text{Income})$. Standard errors are clustered by year-month, and are robust to heteroskedasticity. T-statistics are shown in parentheses.

	PSTK	Invest	Invest Share
Income Rank	0.031 (26.20)	0.134 (82.56)	0.073 (10.09)
College Degree	0.072 (25.54)	0.104 (25.73)	0.289 (19.74)
PSTK		0.176 (24.34)	0.491 (20.41)
Observations	56747	56361	33762
Adjusted R^2	0.113	0.277	0.247

Table 3.9: SES effects on investment decisions, direct and indirect through expectations about future returns in the US stock market.

Model	Direct	Indirect	Total	Indirect/Total
Invest: Income	0.134	0.005	0.139	3.93%
Invest: Education	0.104	0.013	0.117	10.84%
Invest Share: Income	0.073	0.015	0.089	17.21%
Invest Share: Education	0.289	0.035	0.324	10.92%

3.6 Supplementary Results

3.6.1 Time variation in other macroeconomic beliefs by SES

Figure 3.6: UNEMP by SES, over time

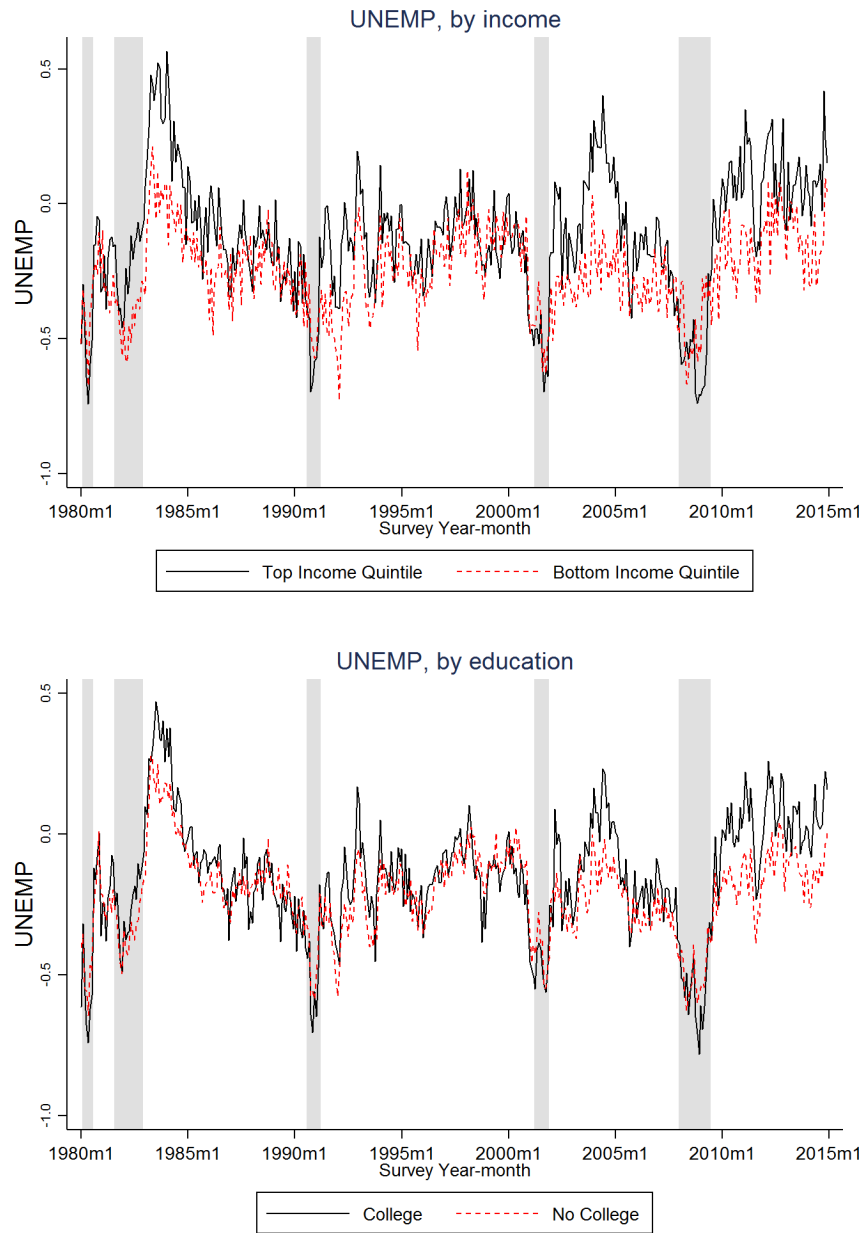


Figure 3.7: BUS12 by SES, over time

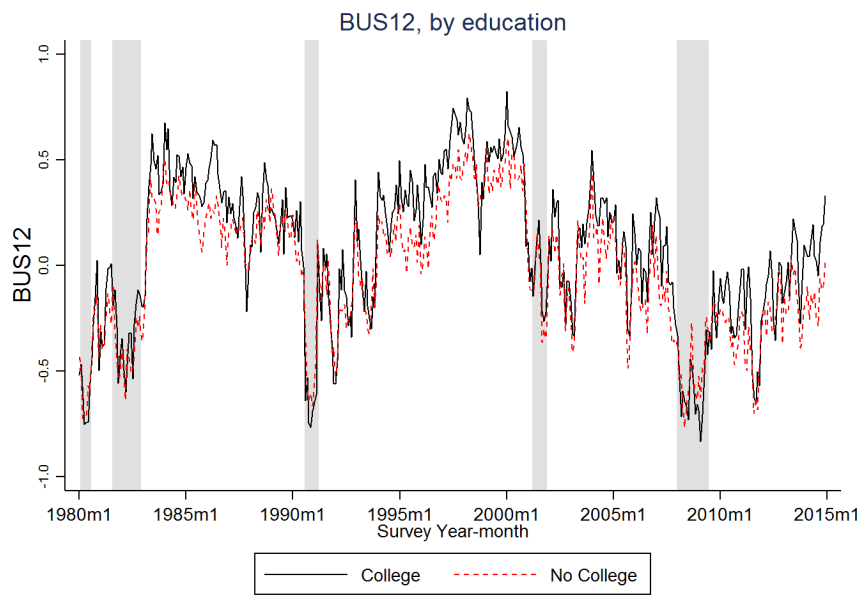
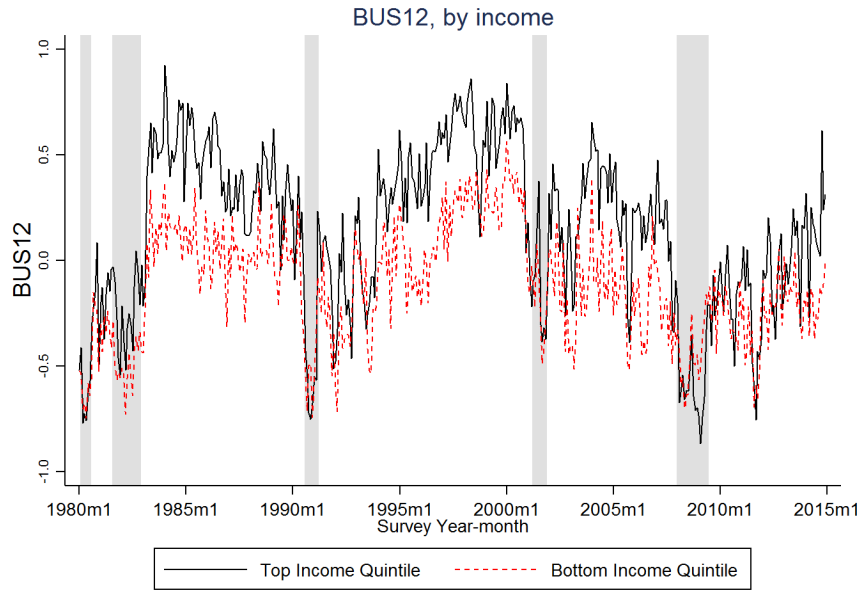


Figure 3.8: BUS5 by SES, over time

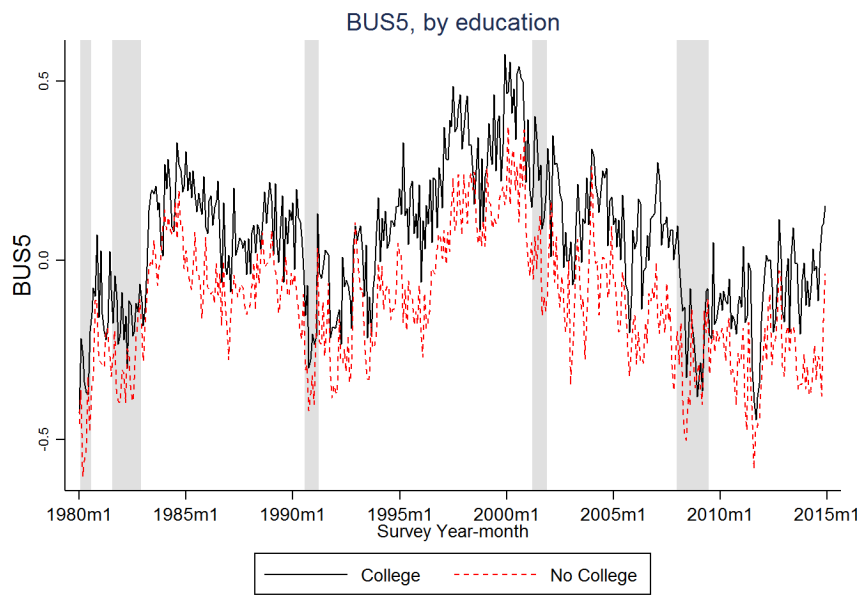
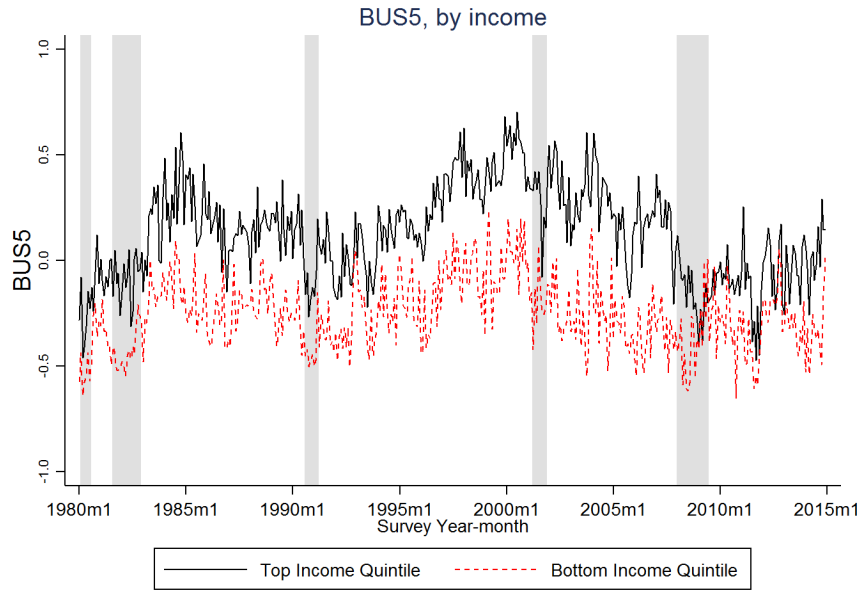
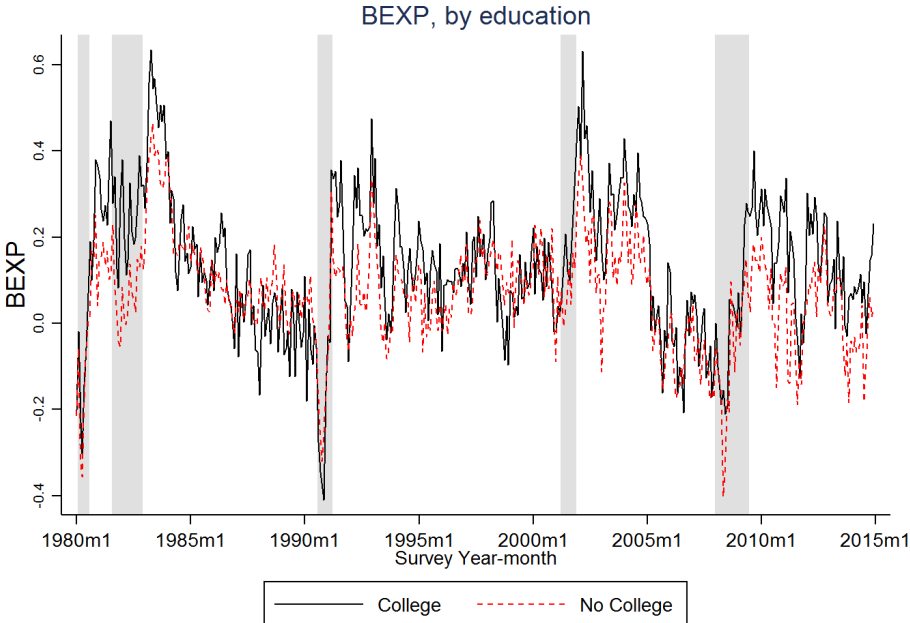
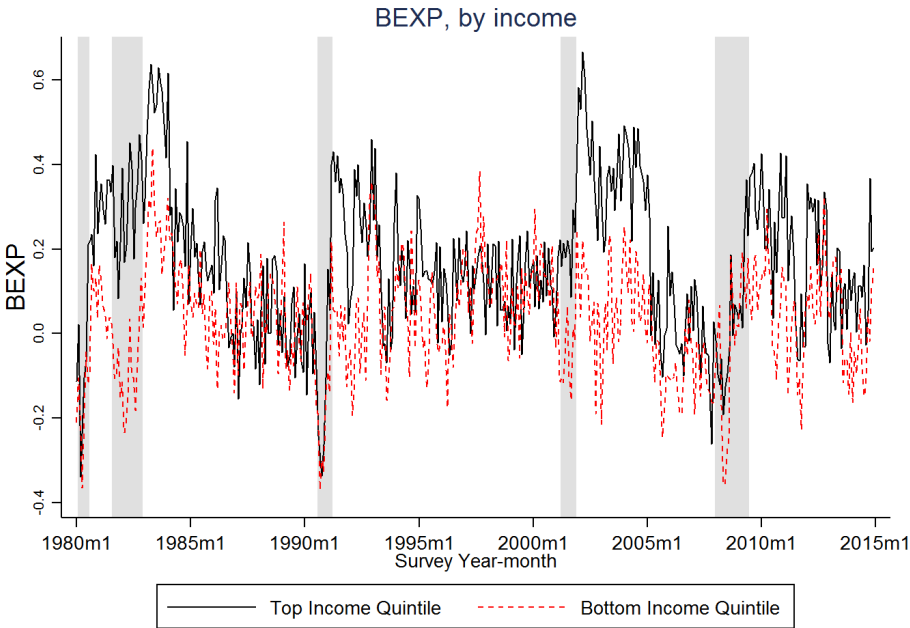


Figure 3.9: BEXP by SES, over time



3.6.2 Instrumental variable estimation of the effect of PSTK on investment choices

In the main body of the paper we study the effect of stock market-related expectations ($PSTK$) on investment decisions (see Table 3.8). Since there we focus on one dimension of beliefs rather than on an aggregate measure based on several macroeconomic beliefs (i.e., $OPTINDEX$), an important issue is that there may be substantial measurement error in the $PSTK$ variable. We used an instrumental variables estimation strategy to address this concern. Consider the following model for the decision to invest in stocks:

$$invest = f(SES, PSTK^*, \eta) \quad (3.1)$$

$$PSTK^* = g'SES + u \quad (3.2)$$

where $invest$ equals 1 if the household participates in the stock market, $PSTK^*$ is the true belief about positive stock returns and η and u are random noise. Assume the observed stock market belief $PSTK$ has measurement error e_1 .

$$PSTK = g'SES + u + e_1 \quad (3.3)$$

The measurement error in observed stock belief induces endogeneity as the error term in Eq (3.1) becomes a function of η and e_1 . We can instrument the noisy observed belief with other observed beliefs in the data but the instrument should be such that there is no correlation between the measurement errors. Consider another belief variable, x ,

with measurement error e_2 .

$$x = w'SES + v + e_2 \tag{3.4}$$

To use x as an instrument, we assume $\text{Corr}(e_1, e_2)=0$ and $\text{Corr}(\eta, v)=0$. Other reported macro belief variables in the Michigan Survey like *BUS12*, *BUS5*, *BEXP* and *UNEMP* could be used as an instrument for *PSTK* assuming their measurement errors are uncorrelated. We use the same IV strategy for analyzing both the decision to invest in stocks, as well as the share of income invested by the household.

In the first stage of the IV regression, for both decisions – whether to invest, and what fraction of income to invest in stocks, we find as expected, that our belief instruments, *BUS12*, *BUS5*, *BEXP* and *UNEMP* are strongly and positively related to the stock market related belief *PSTK*. The IV estimate of the coefficient on *PSTK* is positive and significant and implies that a 1% increase in this belief is associated with a 0.2% increase in the stock market participation rate. The IV coefficient estimate is somewhat larger than the OLS estimate (0.22 vs. 0.17, see Table 3.8) but the direction and magnitude of these effects is similar. We also estimate a linear regression of log amount invested scaled by income on the SES variables and *PSTK*, instrumented as before. The coefficient on *PSTK* indicates that 1% increase in *PSTK* is associated with a 0.90% increase in the fraction of income invested, broadly similar to the OLS estimate in Table 3.8.

BIBLIOGRAPHY

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Acemoglu, D., A. E. Ozdaglar, and A. Tahbaz-Salehi (2015), Systemic risk in endogenous financial networks, *Available at SSRN 2553900*.

Acharya, V., R. Engle, and M. Richardson (2012), Capital shortfall: A new approach to ranking and regulating systemic risks, *The American Economic Review*, pp. 59–64.

Acharya, V. V., and H. Naqvi (2016), On reaching for yield and the coexistence of bubbles and negative bubbles, *Working Paper*. <http://dx.doi.org/10.2139/ssrn.2618973>.

Adrian, T., and M. K. Brunnermeier (2011), Covar, *Tech. rep.*, National Bureau of Economic Research.

Adrian, T., N. Boyarchenko, and O. Shachar (2017), Dealer balance sheets and bond liquidity provision, *FRB of NY Staff Report No. 803*. *SSRN*: <https://ssrn.com/abstract=2891252>.

Ahmed, S., and A. Zlate (2014), Capital flows to emerging market economies: a brave new world?, *Journal of International Money and Finance*, 48, 221–248.

Ait-Sahalia, Y., J. A. Parker, and M. Yogo (2004), Luxury goods and the equity premium, *Journal of Finance*, 59(6).

Allen, F., and D. Gale (1998), Optimal financial crises, *The journal of finance*, 53(4), 1245–1284.

Allen, F., and D. Gale (2000), Financial contagion, *Journal of political economy*, 108(1), 1–33.

Amonlirdviman, K. (2007), Pessimism in household macroeconomic expectations, *Working paper*.

Andersen, S., and K. M. Nielsen (2011), Participation constraints in the stock market: Evidence from unexpected inheritance due to sudden death, *Review of Financial Studies*, 24(5), 1667–1697.

- Aragon, G. O., L. Li, and J. Qian (2016), Counterparty risk in bond mutual funds: Evidence from credit default swaps positions, *SSRN: <https://ssrn.com/abstract=2864425>*.
- Arora, V., and M. Cerisola (2001), How does us monetary policy influence sovereign spreads in emerging markets?, *IMF Economic Review*, 48(3), 474–498.
- Ashcraft, A. B., P. Goldsmith-Pinkham, and J. I. Vickery (2010), Mbs ratings and the mortgage credit boom.
- Babus, A. (2013), The formation of financial networks.
- Bai, J., and P. Collin-Dufresne (2013), The cds-bond basis, *AFA 2013 San Diego Meetings Paper. <https://ssrn.com/abstract=2024531>*.
- Barberis, N., A. Shleifer, and J. Wurgler (2005), Comovement, *Journal of Financial Economics*, 75(2), 283–317.
- Barberis, N., R. Greenwood, L. Jin, and A. Shleifer (2015), X-CAPM: An extrapolative capital asset pricing model, *Journal of Financial Economics*, 115(1), 1–24.
- Barigozzi, M., and C. Brownlees (2013), Nets: Network estimation for time series, *Available at SSRN 2249909*.
- Basu, S., and G. Michailidis (2015), Regularized estimation in sparse high-dimensional time series models, *The Annals of Statistics*, 43(4), 1535–1567.
- Basu, S., A. Shojaie, and G. Michailidis (2015), Network granger causality with inherent grouping structure, *Journal of Machine Learning Research*, 16, 417–453.
- Battiston, S., D. D. Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz (2012), Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk, *Journal of Economic Dynamics and Control*, 36(8), 1121–1141.
- Bech, M. L., and E. Atalay (2010), The topology of the federal funds market, *Physica A: Statistical Mechanics and its Applications*, 389(22), 5223–5246.
- Becker, B., and V. Ivashina (2015), Reaching for yield in the bond market, *The Journal of Finance*, 70(5), 1863–1902.
- Benjamini, Y., and Y. Hochberg (1995), Controlling the false discovery rate: a practical and powerful approach to multiple testing, *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 289–300.

- Benjamini, Y., and D. Yekutieli (2001), The control of the false discovery rate in multiple testing under dependency, *Annals of statistics*, pp. 1165–1188.
- Bhandari, A., J. Borovička, and P. Ho (2016), Identifying ambiguity shocks in business cycle models using survey data, *Tech. rep.*, National Bureau of Economic Research.
- Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012a), Econometric measures of connectedness and systemic risk in the finance and insurance sectors, *Journal of Financial Economics*, 104(3), 535–559.
- Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012b), Econometric measures of connectedness and systemic risk in the finance and insurance sectors, *Journal of Financial Economics*, 104(3), 535–559.
- Blasques, F., F. Bräuning, and I. Van Lelyveld (2015), A dynamic network model of the unsecured interbank lending market.
- Borio, C. E., R. N. McCauley, P. McGuire, and V. Sushko (2016), Covered interest parity lost: understanding the cross-currency basis, *BIS Quarterly Review September 2016*. <https://ssrn.com/abstract=2842331>.
- Boss, M., H. Elsinger, M. Summer, and S. Thurner 4 (2004), Network topology of the interbank market, *Quantitative Finance*, 4(6), 677–684.
- Bosworth, B. (2012), Economic consequences of the great recession: Evidence from the panel study of income dynamics, *Tech. rep.*, Boston College Center for Retirement Research.
- Bowman, D., J. M. Londono, and H. Sapriza (2015), Us unconventional monetary policy and transmission to emerging market economies, *Journal of International Money and Finance*, 55, 27–59.
- Breiman, L. (1995), Better subset regression using the nonnegative garrote, *Technometrics*, 37(4), 373–384.
- Brownlees, C. T., and R. F. Engle (2015), Srisk: A conditional capital shortfall measure of systemic risk, *Available at SSRN 1611229*.
- Brownlees, C. T., E. Nualart, and Y. Sun (2015), Realized networks, *Available at SSRN 2537986*.
- Brunnermeier, M. K., and J. A. Parker (2005), Optimal expectations, *American Economic Review*, 95(4), 1092–1118.

- Brunnermeier, M. K., and L. H. Pedersen (2009a), Market liquidity and funding liquidity, *Review of Financial studies*, 22(6), 2201–2238.
- Brunnermeier, M. K., and L. H. Pedersen (2009b), Market liquidity and funding liquidity, *Review of Financial studies*, 22(6), 2201–2238.
- Brunnermeier, M. K., A. Simsek, and W. Xiong (2014), A welfare criterion for models with distorted beliefs, *Quarterly Journal of Economics*, 129(4), 1753–1797.
- Bühlmann, P., and S. Van De Geer (2011), *Statistics for high-dimensional data: methods, theory and applications*, Springer Science & Business Media.
- Bühlmann, P., and S. van de Geer (2015), High-dimensional inference in misspecified linear models, *Electronic Journal of Statistics*, 9(1), 1449–1473.
- Cai, Q., S. Deggendorf, and J. A. Wilcox (2015), Building a home purchase sentiment index, *Fannie Mae White Paper*.
- Calvet, L. E., J. Y. Campbell, and P. Sodini (2007), Down or out: Assessing the welfare costs of household investment mistakes, *Journal of Political Economy*, 115(5), 707–747.
- Campbell, J. Y. (2006), Household finance, *Journal of Finance*, 61(4), 1553–1604.
- Carroll, C. D., J. C. Fuhrer, and D. W. Wilcox (1994), Does consumer sentiment forecast household spending? If so, why?, *American Economic Review*, 84(5), 1397–1408.
- Chan-Lau, J. A., M. Espinosa, K. Giesecke, and J. A. Solé (2009), Assessing the systemic implications of financial linkages, *IMF global financial stability report*, 2.
- Chen, Q., A. Filardo, D. He, and F. Zhu (2012), International spillovers of central bank balance sheet policies, *BIS Papers*, 66, 220–264.
- Choi, J., and M. Kronlund (2016), Reaching for yield by corporate bond mutual funds, *Working Paper* <http://dx.doi.org/10.2139/ssrn.2527682>.
- Coibion, O., and Y. Gorodnichenko (2015), Information rigidity and the expectations formation process: A simple framework and new facts, *American Economic Review*, 105(8), 2644–2678.
- Colla, P., and A. Mele (2010), Information linkages and correlated trading, *Review of Financial Studies*, 23(1), 203–246.

- Cordeiro, G. M., and P. McCullagh (1991), Bias correction in generalized linear models, *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 629–643.
- Cordeiro, G. M., and K. L. Vasconcellos (1997), Bias correction for a class of multivariate nonlinear regression models, *Statistics & probability letters*, 35(2), 155–164.
- Craig, B., and G. Von Peter (2014), Interbank tiering and money center banks, *Journal of Financial Intermediation*, 23(3), 322–347.
- Csonto, M. B., and M. I. V. Ivaschenko (2013), *Determinants of sovereign bond spreads in emerging markets: Local fundamentals and Global factors vs. Ever-changing misalignments*, 13-164, International Monetary Fund.
- Curtin, R., and P. Dechaux (2015), University of michigan’s survey of consumers: Measuring and interpreting economic expectations, *Tech. rep.*, University of Michigan.
- Curtin, R., S. Presser, and E. Singer (2002), The impact of nonresponse bias on the index of consumer sentiment, *Economic Surveys and Data Analysis*, pp. 307–323.
- Dezeure, R., P. Bühlmann, L. Meier, N. Meinshausen, et al. (2015), High-dimensional inference: Confidence intervals, p -values and r-software hdi, *Statistical Science*, 30(4), 533–558.
- Di Maggio, M., and M. Kacperczyk (2017), The unintended consequences of the zero lower bound policy, *Journal of Financial Economics*, 123(1), 59–80.
- Diamond, D. W., and P. H. Dybvig (1983), Bank runs, deposit insurance, and liquidity, *Journal of political economy*, 91(3), 401–419.
- Diebold, F. X., and K. Yilmaz (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics*, 182(1), 119–134.
- Dominitz, J., and C. F. Manski (2007), Expected equity returns and portfolio choice: Evidence from the health and retirement study, *Journal of the European Economic Association*, 5(2-3), 369–379.
- Du, W., A. Tepper, and A. Verdelhan (2016), Deviations from covered interest rate parity, *SSRN: <https://ssrn.com/abstract=2768207>*.
- Duffie, D. (1999), Credit swap valuation, *Financial Analysts Journal*, pp. 73–87.

- Duffie, D. (2010), Presidential address: Asset price dynamics with slow-moving capital, *The Journal of finance*, 65(4), 1237–1267.
- Duffie, D., N. Gârleanu, and L. H. Pedersen (2005), Over-the-counter markets, *Econometrica*, 73(6), 1815–1847.
- Eichengreen, B., and A. Mody (1998), What explains changing spreads on emerging-market debt: fundamentals or market sentiment?, *Tech. rep.*, National Bureau of Economic Research.
- Eichler, M. (2012), Graphical modelling of multivariate time series, *Probability Theory and Related Fields*, 153(1-2), 233–268.
- Engle, R. (2002), Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business & Economic Statistics*, 20(3), 339–350.
- Favilukis, J. (2013), Inequality, stock market participation, and the equity premium, *Journal of Financial Economics*, 107(3), 740–759.
- Fontana, A. (2011), The negative cds-bond basis and convergence trading during the 2007/09 financial crisis, *Swiss Finance Institute Research Paper No. 11-41*. <http://dx.doi.org/10.2139/ssrn.1939184>.
- Fontana, A., and M. Scheicher (2016), An analysis of euro area sovereign cds and their relation with government bonds, *Journal of Banking & Finance*, 62, 126–140.
- Forbes, K. J., and R. Rigobon (2002), No contagion, only interdependence: measuring stock market comovements, *The journal of Finance*, 57(5), 2223–2261.
- Fratzscher, M., M. Lo Duca, and R. Straub (2016), On the international spillovers of us quantitative easing, *The Economic Journal*.
- Friedman, J., T. Hastie, and R. Tibshirani (2008), Sparse inverse covariance estimation with the graphical lasso, *Biostatistics*, 9(3), 432–441.
- Garleanu, N., and L. H. Pedersen (2011), Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies*, 24(6), 1980–2022.
- Garleanu, N., L. H. Pedersen, and A. M. Poteshman (2009), Demand-based option pricing, *Review of Financial Studies*, 22(10), 4259–4299.
- Geanakoplos, J. (2009), The leverage cycle, in *NBER Macroeconomics Annual*, edited by D. Acemoglu, K. Rogoff, and M. Woodford.

- Gennaioli, N., and A. Shleifer (2010), What comes to mind, *Quarterly Journal of Economics*, 125(4), 1399–1433.
- Gennaioli, N., A. Shleifer, and R. Vishny (2015), Neglected risks: The psychology of financial crises, *American Economic Review: Papers & Proceedings*, 105(5), 310–314.
- Gertler, M., and P. Karadi (2015), Monetary policy surprises, credit costs, and economic activity, *American Economic Journal: Macroeconomics*, 7(1), 44–76.
- Gilchrist, S., E. Zakrajek, and V. Z. Yue (2014), The response of sovereign bond yields to u.s. monetary policy, *Paper presented at the 15th Jacques Polak Annual Research Conference* http://www.imf.org/external/np/res/seminars/2014/arc/pdf/gilchrist_yue_zakrajsek.pdf.
- Glasserman, P., and H. P. Young (2015), How likely is contagion in financial networks?, *Journal of Banking & Finance*, 50, 383–399.
- Gofman, M. (2016), Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions, *Available at SSRN 2194357, Forthcoming in Journal of Financial Economics*.
- Gomez, M. (2017), Asset prices and wealth inequality, *Working paper*.
- Granger, C. W. (1969), Investigating causal relations by econometric models and cross-spectral methods, *Econometrica: Journal of the Econometric Society*, pp. 424–438.
- Granger, C. W. (1980), Testing for causality: a personal viewpoint, *Journal of Economic Dynamics and control*, 2, 329–352.
- Greenwood, R., and A. Shleifer (2014), Expectations of returns and expected returns, *Review of Financial Studies*, 27(3), 714–746.
- Guettler, A., and T. Adam (2010), The use of credit default swaps by us fixed-income mutual funds, *FDIC Center for Financial Research Working Paper No. 2011-01*.
- Gurkaynak, R. S., B. Sack, and E. T. Swanson (2005), Do actions speak louder than words? the response of asset prices to monetary policy actions and statements, *International Journal of Central Banking*, 1(1), 55–93.
- Guvenen, F., S. Ozkan, and J. Song (2014), The nature of countercyclical income risk, *Journal of Political Economy*, 122(3), 621–660.

- Guvenen, F., S. Schulhofer-Wohl, J. Song, and M. Yogo (2017), Worker betas: Five facts about systematic earnings risk, *American Economic Review: Papers & Proceedings*.
- Guzman, M. M., and J. E. Stiglitz (2015), Pseudo-wealth and consumption fluctuations, *Tech. rep.*, Columbia University.
- Haltom, R. C., et al. (2013), Reaching for yield, *Econ Focus*, (3Q), 5–8.
- Hansen, L. P., and T. J. Sargent (2016), Sets of models and prices of uncertainty, *Tech. rep.*, National Bureau of Economic Research.
- Hanson, S. G., and J. C. Stein (2015), Monetary policy and long-term real rates, *Journal of Financial Economics*, 115(3), 429–448.
- Iori, G., G. De Masi, O. V. Precup, G. Gabbi, and G. Caldarelli (2008), A network analysis of the italian overnight money market, *Journal of Economic Dynamics and Control*, 32(1), 259–278.
- Jankova, J., S. van de Geer, et al. (2015), Confidence intervals for high-dimensional inverse covariance estimation, *Electronic Journal of Statistics*, 9(1), 1205–1229.
- Jarrow, R. A. (2011), The economics of credit default swaps, *Annu. Rev. Financ. Econ.*, 3(1), 235–257.
- Jarrow, R. A. (2016), *The Economic Foundations of Risk Management: Theory, Practice, and Applications*, World Scientific Press.
- Javanmard, A., and A. Montanari (2014), Confidence intervals and hypothesis testing for high-dimensional regression, *The Journal of Machine Learning Research*, 15(1), 2869–2909.
- Jiang, W., and Z. Zhu (2016), Mutual fund holdings of credit default swaps: Liquidity management and risk taking, *Columbia Business School Research Paper No. 16-21*. <http://dx.doi.org/10.2139/ssrn.2736633>.
- Kamin, S. B., and K. Von Kleist (1999), The evolution and determinants of emerging markets credit spreads in the 1990s, *BIS Working Paper No. 68*. <http://dx.doi.org/10.2139/ssrn.850104>.
- Karolyi, G. A., and K. J. McLaren (2016), Racing to the exits: International transmissions of funding shocks during the federal reserve’s taper experiment, <https://ssrn.com/abstract=2792347>.

- Kearney, M. S., and P. B. Levine (2016), Income inequality, social mobility, and the decision to drop out of high school, *Brookings Papers on Economic Activity, Spring*, 333–396.
- Kezdi, G., and R. J. Willis (2011), Household stock market beliefs and learning, *NBER Working Paper No. 17614*.
- Klingler, S., and S. M. Sundaresan (2016), An explanation of negative swap spreads: demand for duration from underfunded pension plans, <https://ssrn.com/abstract=2814975>.
- Koepke, R. (2015), Fed policy expectations and portfolio flows to emerging markets, *Working paper*. <http://dx.doi.org/10.2139/ssrn.2456288>.
- Krishnamurthy, A., and A. Vissing-Jorgensen (2011), The effects of quantitative easing on interest rates: channels and implications for policy, *Tech. rep.*, National Bureau of Economic Research.
- Kuchler, T., and B. Zafar (2016), Personal experiences and expectations about aggregate outcomes, *Tech. rep.*, New York University.
- Kuhnen, C. M. (2015), Asymmetric learning from financial information, *Journal of Finance*, 70(5), 2029–2062.
- Kuhnen, C. M., and A. C. Miu (2017), Socioeconomic status and learning from financial information, *Journal of Financial Economics*.
- Le Cam, L. (1956), On the asymptotic theory of estimation and testing hypotheses, in *Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*, The Regents of the University of California.
- Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton (2011), How sovereign is sovereign credit risk?, *American Economic Journal: Macroeconomics*, 3(2), 75–103.
- Lütkepohl, H. (2005), *New introduction to multiple time series analysis*, Springer.
- Malmendier, U., and S. Nagel (2011), Depression babies: Do macroeconomic experiences affect risk-taking?, *Quarterly Journal of Economics*, 126, 373–416.
- Malmendier, U., and S. Nagel (2015), Learning from inflation experiences, *Quarterly Journal of Economics*, p. forthcoming.
- Malmendier, U., and G. Tate (2005), Ceo overconfidence and corporate investment, *Journal of Finance*, 60(6), 2661–2700.

- Malmendier, U., G. Tate, and J. Yan (2011), Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance*, 66(5), 1687–1733.
- Mankiw, N. G., R. Reis, and J. Wolfers (2003), Disagreement about inflation expectations, in *NBER Macroeconomics Annual 2003*, edited by M. Gertler and K. Rogoff.
- Manski, C. F. (2004), Measuring expectations, *Econometrica*, pp. 1329–1376.
- McGuire, P., and M. A. Schrijvers (2003), Common factors in emerging market spreads, *BIS Quarterly Review*. <https://ssrn.com/abstract=1968450>.
- Meinshausen, N., and P. Bühlmann (2006), High-dimensional graphs and variable selection with the lasso, *Ann. Statist.*, 34(3), 1436–1462, doi:10.1214/009053606000000281.
- Miranda-Agrippino, S., and H. Rey (2015), World asset markets and the global financial cycle, *Tech. rep.*, National Bureau of Economic Research.
- Mishra, P., K. Moriyama, P. M. N’Diaye, L. Nguyen, et al. (2014), Impact of fed tapering announcements on emerging markets, *Tech. rep.*, International Monetary Fund.
- Mitchell, M., and T. Pulvino (2012), Arbitrage crashes and the speed of capital, *Journal of Financial Economics*, 104(3), 469–490.
- Nashikkar, A., M. G. Subrahmanyam, and S. Mahanti (2011), Liquidity and arbitrage in the market for credit risk, *Journal of Financial and Quantitative Analysis*, 46(03), 627–656.
- Oehmke, M., and A. Zawadowski (2015), Synthetic or real? the equilibrium effects of credit default swaps on bond markets, *Review of Financial Studies*, 28(12), 3303–3337.
- Oehmke, M., and A. Zawadowski (2017), The anatomy of the cds market, *Review of Financial Studies*, 30(1), 80–119.
- Parker, J. A., and A. Vissing-Jorgensen (2009), Who bears aggregate fluctuations and how?, *American Economic Review: Papers & Proceedings*, 99(2), 399–405.
- Parker, J. A., and A. Vissing-Jorgensen (2010), The increase in income cyclicality of high-income households and its relation to the rise in top income shares, *NBER Working Paper 16577*.

- Piazzesi, M., and M. Schneider (2012), Inflation and the price of real assets, *Tech. rep.*, Stanford University.
- Puri, M., and D. T. Robinson (2007), Optimism and economic choice, *Journal of Financial Economics*, 86(1), 71–99.
- Rai, V., and L. Suchanek (2014), The effect of the federal reserves tapering announcements on emerging markets, *Tech. rep.*, Bank of Canada.
- Rajan, R. G. (2006), Has finance made the world riskier?, *European Financial Management*, 12(4), 499–533.
- Ravikumar, P., M. J. Wainwright, G. Raskutti, and B. Yu (2011), High-dimensional covariance estimation by minimizing 1-penalized log-determinant divergence, *Electronic Journal of Statistics*, 5, 935–980.
- Saez, E. (2015), Striking it richer: The evolution of top incomes in the united states (updated with 2013 preliminary estimates), *Tech. rep.*, UC Berkeley.
- Shachar, O. (2012), Exposing the exposed: Intermediation capacity in the credit default swap market, *Working Paper*.
- Sims, C. A. (2008), Inflation expectations, uncertainty, and monetary policy, *Tech. rep.*, Princeton University.
- Siriwardane, E. (2016), Concentrated capital losses and the pricing of corporate credit risk, *Harvard Business School Finance Working Paper No. 16-007*. <http://dx.doi.org/10.2139/ssrn.2584043>.
- Soramäki, K., M. L. Bech, J. Arnold, R. J. Glass, and W. E. Beyeler (2007), The topology of interbank payment flows, *Physica A: Statistical Mechanics and its Applications*, 379(1), 317–333.
- Souleles, N. S. (2004), Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan Consumer Sentiment Surveys, *Journal of Money, Credit, and Banking*, 36(1), 39–72.
- Stein, J. C. (2013), Overheating in credit markets: origins, measurement, and policy responses, *Speech at research symposium sponsored by the Federal Reserve Bank of St. Louis*. <https://www.federalreserve.gov/newsevents/speech/stein20130207a.htm>.
- Sun, T., and C.-H. Zhang (2012), Scaled sparse linear regression, *Biometrika*, p. ass043.

- Tibshirani, R. (1996), Regression shrinkage and selection via the lasso, *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 267–288.
- van de Geer, S., and B. Stucky (2016), χ^2 -confidence sets in high-dimensional regression, in *Statistical Analysis for High-Dimensional Data*, pp. 279–306, Springer.
- van de Geer, S., P. Bühlmann, Y. Ritov, and R. Dezeure (2014), On asymptotically optimal confidence regions and tests for high-dimensional models, *The Annals of Statistics*, 42(3), 1166–1202.
- Vissing-Jorgensen, A. (2002), Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structure, *Tech. rep.*, UC Berkeley.
- Vissing-Jorgensen, A. (2003), Perspectives on behavioral finance: Does "irrationality" disappear with wealth? evidence from expectations and actions, in *NBER Macroeconomics Annual*.
- Wainwright, M. J., and M. I. Jordan (2008), Graphical models, exponential families, and variational inference, *Foundations and Trends® in Machine Learning*, 1(1-2), 1–305.
- Yellen, J. L., et al. (2011), Assessing potential financial imbalances in an era of accommodative monetary policy: a speech at the 2011 international conference: Real and financial linkage and monetary policy, bank of japan, tokyo, japan, june 1, 2011, *Tech. rep.*
- Zhang, C.-H., and S. S. Zhang (2014), Confidence intervals for low dimensional parameters in high dimensional linear models, *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 76(1), 217–242.