Flight to Safety in Business cycles

Yadav, Jayant

University of Glasgow, Adam Smith Business School, Department of Economics

31 October 2020

PhD Thesis Chapter
Flight to Safety in Business cycles

Jayant Yadav

Tuesday 12th January, 2021

Acknowledgements

I am grateful to ESRC-UK Scottish DTC Grant No. ES/J500136/1 for providing financial support for this thesis.

FTS in Business cycles examines the dynamic effects and empirical significance of Flight to Safety (FTS) shocks in the context of US business cycles. FTS represents a sudden preference for safe over risky investments and contains important information on agents' time varying risk-aversion and their expectations for future economic activity. This analysis presents an identification for FTS shocks using vector autoregressions (VAR). Sign restrictions are applied, while controlling for monetary policy and productivity shocks, on the price differential series between stocks and bonds in the US. Identified positive disturbances to this differential series are characterised as FTS shocks. The business cycle impact of FTS is calculated by applying the structural VAR model to the US economic data from 1954 to 2019. A sudden increase in risk aversion, which is displayed through the FTS shocks in the identified VAR model, has played a significant role in keeping investments low in the US. FTS shocks explain more than sixty percent of the variation in US investments and they explain a higher proportion of macroeconomic fluctuations in periods around the Global financial crisis. This is a significant linkage when compared against results of DSGE models enriched with time-varying risk-premium and investment technology. FTS also comes up ahead of news shocks in providing early signals of shifts in total factor productivity. This analysis is consistent with other comparable high-frequency, kernel-based measures of identifying FTS. The results also reveal the asymmetric impact on the business cycle of Flight to Safety and its complement Flight to Risk phenomenon. This asymmetry lends support to pursuing a cyclical risk-aversion driven view of business cycles.

1 Introduction

How can we identify Flight to Safety shocks? Do they have any significant effect on the economy and the business cycles? Does the Flight to Safety phenomenon warrant much attention if the shift of investments from risky to safe assets over one week reverses in the next week? These are some important questions of interest to both investors and policymakers alike. This chapter proposes answers to these and similar questions using sign-based restrictions in identifying the Flight to Safety shocks through vector autoregressions. Doing so also opens up new avenues to improve our understanding of macroeconomic shocks and their propagation mechanisms in business cycles.

The Flight to Safety shocks in this chapter represent unexpected positive innovations to households' risk aversion, or these are the shocks that lower investor's risk appetite. There are many instances in the financial markets, e.g. the Lehman crisis period and the Covid-19 period, when an increase in risk aversion and uncertainty has led to bursts of flight of investment capital from risky to safe assets. Such instances are commonly referred to as Flight to Safety (FTS). Similarly, any unexpected reduction in risk aversion, which then motivates a flight of investment capital in the reverse direction, i.e., from safe to risky assets, is known as Flight to Risk (FTR). This chapter investigates the impact and transmission of innovations to investors' risk aversion on financial markets, macroeconomic aggregates, and business cycles through the medium of Flight to Safety shocks.

The method for identifying Flight to Safety shocks in this chapter builds on Uhlig's (2005) agnostic identification strategy of imposing sign restrictions on the impulse response functions. This method identifies Flight to Safety shocks in a five variable structural vector autoregressions (S-VAR) model by imposing sign restrictions on impulse responses in four out of five macroeconomic series of the S-VAR, *viz.* TFP, price of risk, real rates, and surplus ratio. The TFP is adjusted for factor-utilization (Fernald, 2012). The price of risk series is obtained by differencing the S&P 500 index price from the price of long-term US treasury bonds. Any upside shift in this price of risk series will result from US Treasury bonds becoming expensive vis-à-vis US equities, which represents Flight to Safety. Real policy rates are obtained by adjusting effective federal funds rates for the rate of inflation. The surplus ratio is defined for this chapter[1] as one minus ratio

[1]The later chapters, which feature an NK model with internal habits, define surplus ratio differently as one minus ratio of subsistence habits to consumption. **??** on page **??** provides the

of the sum of non-durable goods and services consumption to total consumption. FTS shocks are identified by imposing orthogonality (or zero) restrictions between Flight to Safety and generic business cycle disturbances. The latter are shocks to the utilization-adjusted total factor productivity series and are ordered first in the five variable S-VAR. The fifth series that is ordered last in the S-VAR is a business cycle variable of interest (such as output, hours or investment, etc.). No restrictions are imposed on its impulse responses to any shocks in the model. In this manner, the identification method remains agnostic to the key variable of interest. Different sign restrictions, from the ones imposed to identify the FTS shocks, are included to single out the utilization-adjusted total factor productivity (TFP) shocks, and monetary policy (MP) shocks. These two disturbances are also restricted as orthogonal to each other.

The identification strategy is designed to overcome many challenges that are expected to arise in identifying the Flight to Safety shocks in vector autoregressions. At first, there is confusion over what one means by Flight to Safety shocks. There is no standard definition of the Flight to Safety phenomenon, and there is no actual price of risk series from which we can extract Flight to Safety shocks. The second concern is about the validity of the entire econometric procedure, which relates to whether the shocks in the price of risk series are purely led from a Flight to Safety (or Risk) motive or automatic movements resulting from other demand, business cycle, or monetary policy shocks. The next concern is avoiding the possibility that external shock impacts all variables in the model. Several shocks come to mind, which could have effects similar to those of a business cycle shock or a Flight to Safety shock. However, they result from sources exogenous to the model, e.g., a labour supply shock in another sector, an oil price shock, a fiscal policy shock. The fourth concern pertains to the choice of sign restrictions imposed and the credibility of identifying assumptions employed in this study. There may be agreement about some sign restrictions strategies, e.g., that positive monetary policy shocks raise interest rates in the short run. However, competing ideas come to mind when considering the impact of Flight to Safety on various macroeconomic time series. Finally, one also needs to consider that this study's results represent the impact of the intended Flight to Safety shocks and are not resulting from any other form of expectations, policy uncertainty, or sentiment shocks in disguise.

The first concern can be addressed by arguing that Flight to Safety is a phenomenon of forward looking expectations and that households prefer bonds

definitions for use in later chapters.

or safer assets to equities or riskier assets, to safeguard their portfolio against expected loss of future income and wealth. By following this approach, we can obtain a price of risk series from the difference between the price of safe securities, which for this chapter is calculated by inverting the yield on 10-year US Treasury bonds and the price of risky securities (or the S&P 500 index). This price of risk series increases (or moves up) when investors favour safer investments (bonds) more than riskier investments (equities).

Developing a price of risk series in this manner has a clear advantage over other recent attempts in the literature to identify the incidence of Flight to Safety using likelihood and kernel-based methods. For e.g. Baele, Bekaert, Inghelbrecht, and Wei (2013 and 2019). The approach to developing the price of risk series followed in this chapter provides a smooth trend stationary series suitable for vector autoregressions. It can be replicated without relying on the researcher's inputs of the bandwidth and threshold criteria, as required in likelihood and kernel-based methods. The Sensitivity analysis section compares the Flight to Safety shocks obtained using methods of Baele, Bekaert, Inghelbrecht, and Wei (2019) with the Flight to Safety shocks obtained through S-VAR. These two procedures' key results are comparable, but working out a Flight to Safety series through VAR offers ease of replication and universal appeal.

For addressing the second concern, the orthogonality restriction imposed between total factor productivity shocks and Flight to Safety shocks filters out the possibility of automatic spillovers from business cycle surprises to Flight to Safety shocks. Orthogonality restriction between total factor productivity shocks and monetary policy shocks is also vital to keeping monetary shocks unrelated to generic movements in business cycles.

The third concern is addressed by repeating this exercise for other macro variables. The benchmark configuration's key variable of interest in subsequent experiments is replaced with other business cycle variables (such as hours, foreign portfolio flows, consumer prices, etc.). The purpose of such an examination is to seek common plausible explanations for changes in impulse responses between the replacement model and the benchmark S-VAR model and to avoid missing out on any explanatory contribution from common external factors.

The fourth concern is resolved by choosing policy-relevant and theoretically robust signs and zero restrictions. The identifying assumptions are based on the results of Smets and Wouters (2007). They consider a medium scale NK or

NNS (New Neoclassical synthesis) model that is consistent with the balanced steady-state growth path and is estimated using Bayesian methods. Their model has 7 structural shocks in: total factor productivity, risk premium, investment technology, wage, price markup, exogenous spending, and monetary policy. Several features of their model such as labour augmenting technological progress, investment adjustment costs, variable capacity utilization, and real rigidity in intermediate goods and labour market, make it a standard workhorse model of monetary policy analysis and also make it relevant for obtaining economic theory backed sign restrictions for total factor productivity, Flight to Safety and monetary policy shocks for the analysis made in this chapter.

Some of the critical results from Smets and Wouters (2007) that are useful in driving sign restrictions for this chapter are as follows. Technology shocks lead to an increase in output and consumption but a small decrease in nominal and real interest rates. On the initial impact, the fall in real rates is insufficient to prevent a decline in inflation and opening up of the output gap. Flight to Safety shocks restrictions in this chapter follow from risk premium shocks of Smets and Wouters (2007) where these innovations result in a fall in output, hours, and an increase in the real interest rate. One could argue that the risk premium shocks are not the same as a Flight to Safety shocks. Nevertheless, suppose the increase in risk premium is not uniform across investments of different risk profiles. In that case, for this chapter and to generate comparable results with standard DSGE models, it is within reason to characterize an increase in risk premium as a motivating factor for investors' preference for safety. The monetary policy shocks in that model (Smets and Wouters, 2007) on impact lead to an increase in nominal and real interest rates but a decrease in output, inflation, and hours. The monetary policy shocks in S-VAR model of this chapter include similar restrictions.

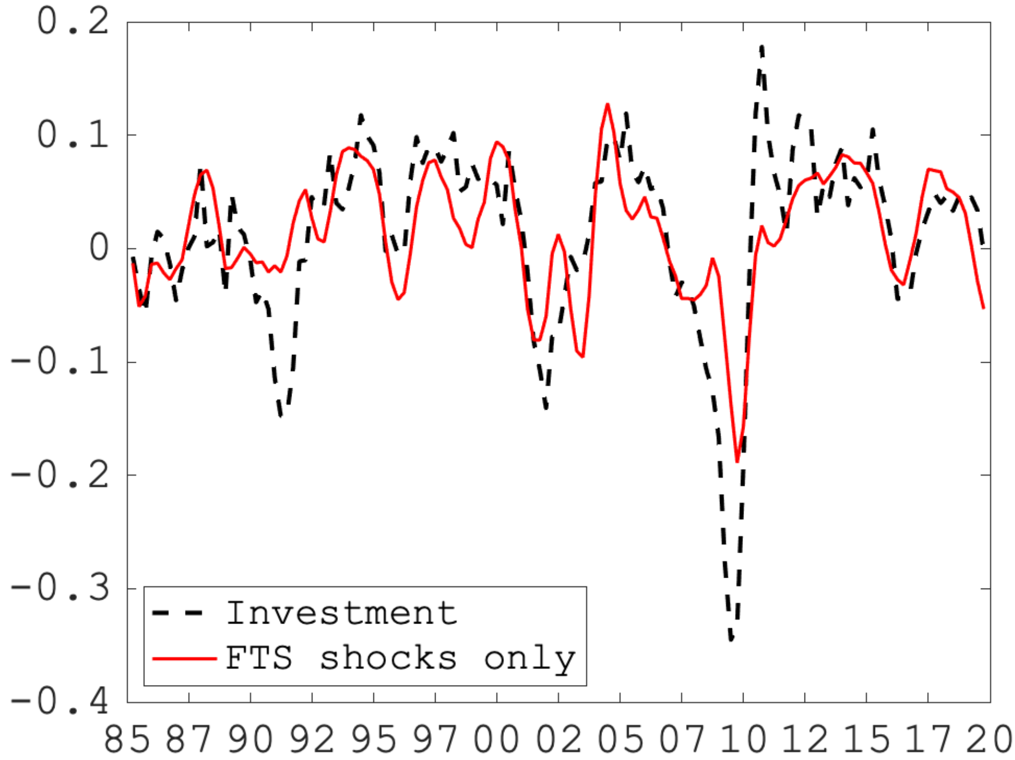
The fifth and final concern is addressed in the robustness section, where results from the economic policy uncertainty series [from Baker, Bloom, and Davis (2016) and Bloom (2014)], corporate bonds spread, liquidity spread, investment-specific technological productivity, and the relative price of the investment in terms of consumption are included in the analysis. Their results depict a reasonable likeness between the share of investment growth explained through Flight to Safety shocks and other series that capture the phenomenon of Flight to Safety. The Granger causality running from the price of risk series to these alternate series reaffirms the notion that Flight to Safety plays a significant role in business cycles.

The analysis contributes by motivating us to rethink about the role played by Flight to Safety in the most severe US recession since the Great depression. This chapter's empirical exercise extends research on Flight to Safety into new directions in the following manner. Firstly, it explores the long and short-run impact of Flight to Safety shocks on key macroeconomic variables through a structural vector autoregression study where Flight to Safety and monetary policy shocks are orthogonal to any business cycle shocks. The structural VAR makes minimal assumptions about the existence of any prior ordering of structural shocks. Secondly, it evaluates the strength of results by comparing them with the business cycle phenomenon in other sectors such as labour market and investments and in different periods such as the Great moderation period running up to the global financial crisis and the pre-Great moderation period. Thirdly, it evaluates the empirical exercise and identification strategy by obtaining comparable results from series that, in principle, have similar impact phenomena as the Flight to Safety. Some of the other asset market phenomena that coincide with episodes of FTS are: an increase in policy uncertainty, a widening of yield spreads between Baa and Aaa corporate bonds yields, an increase in liquidity spread between the yields on long-term and short-term treasury bonds, and an increase in the ratio of the price of investment goods to the price of consumption goods. The Robustness section makes a comparison between each series' business cycle impacts with the results obtained from the FTS series. Fourthly, the analysis brings to light the asymmetric economic impact of Flight to Safety and the capital flight in the reverse direction, Flight to Risk. Lastly, it develops a Flight to Safety shock series for the US economy that is intuitive and simple.

The contribution of results comes from providing a sound justification and closure to the main objective of undertaking this study to estimate the business cycle impact of FTS. Flight to Safety shocks significantly affect the long-term dynamics of the business cycle and economic activity. The impact of Flight to Safety shocks on the economy has increased in the post-Global financial crisis period. Hours, output, consumption, and investments all display negative responses to identified Flight to Safety shocks.

A one standard deviation Flight to Safety shock can account for a statistically significant 3% decline in private investments and a 4% decline in residential investments over a couple of years. Identified FTS shocks also lead to an imminent fall in total factor productivity by 8-10 quarters. Thus, they dispel the notion that FTS shocks are a neutral TFP or investment related TFP shock in disguise. FTS shocks also account for over sixty percent variation in relevant macroeco-

Figure 1: Contribution of FTS to Investment growth



Notes: Y-axis: Year on year growth rate (%) of US Investments and the benchmark model fitted with only Flight to Safety (FTS) shocks identified using Sign and Zero restrictions discussed in Strategy 1. X-axis label is Years (in YY format). Investment - is the US investment data series (PInv). FTS shocks only - is the Investment series in the benchmark model fitted with FTS shocks only.

nomic variables (hours, output, consumption, and investments) at business cycle frequencies, indicating that such shocks are an essential part of business cycles.

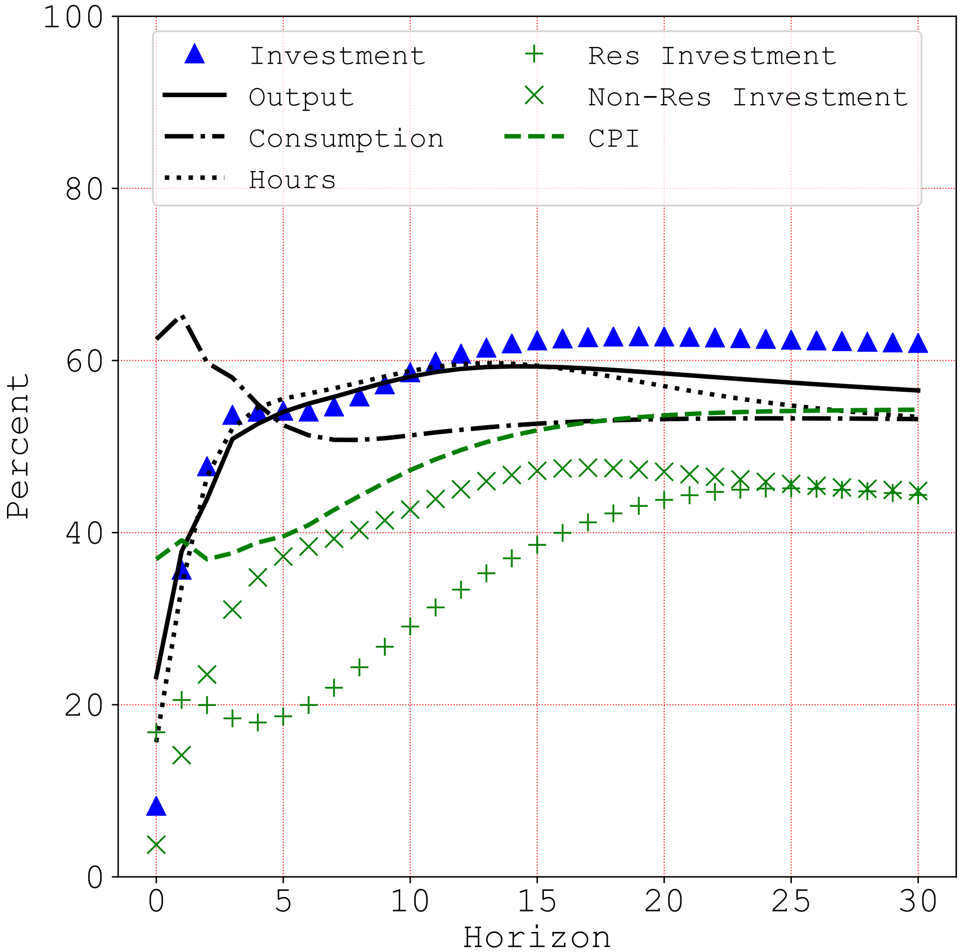
The identified Flight to Safety shocks in the benchmark VAR configuration can explain majority of the historical decomposition of Investments in the US. See Figure 1 on page 9, which plots the year on year growth in the investment data (dashed line) and the one that can be explained by only the Flight to Safety shocks in the benchmark VAR model (solid line). The co-movement between the two series is striking. In particular, during economic downturns such as previous recessions of the 80s, 90s, the Dotcom bust, and the Global financial crisis, the Flight to Safety shocks seem to be running the investment growth lower.

Besides FTS shocks, the benchmark model whose identification restrictions we will discuss in later sections, has shocks in total factor productivity, monetary policy, and consumer demand. Despite the presence of these other three keys shocks such a significant contribution of the Flight to Safety shocks, signifying that perceived risk aversion and precautionary motives manifested in Flight to Safety have a more prominent role in developing our understanding of business cycles. The significant contribution of FTS shocks to business cycles can be further corroborated from the k-period ahead forecast error variance decomposition (from Figure 2 on page 11) of crucial macro variables from identified Flight to Safety shocks. The figure shows that FTS explains more the sixty percent of forecast error variance in investment and a significant portion of it in other key macro variables such as output, hours, CPI, and consumption at business cycle frequency (8-32 quarters).

A breakdown of historical decomposition (Figure 3 on page 12) of the Investment series shows that FTS shocks were a significant driver of the increase in private investments in the years 1994-2007 running up to the global financial crisis. The significance of FTS shocks has been at its maximum during the period following the global financial crisis. Post-2009, there is a sluggish response of Investment series in the US due to negative FTS shocks hitting the economy. The recovery period had a reduced incidence of FTS shocks, but only after 2015 did we see any positive deviation from the Investment series trend.

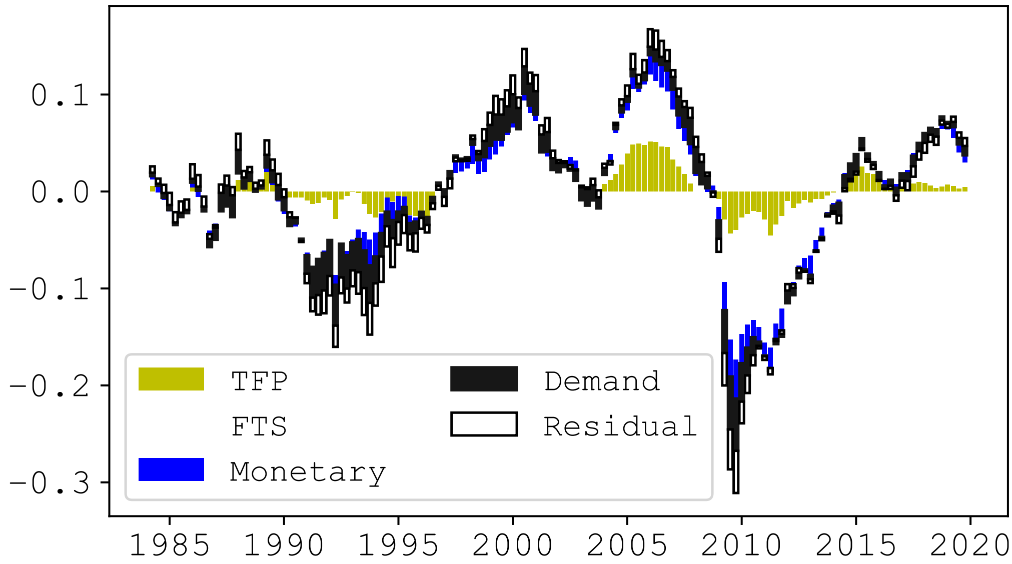
An underlying expectation hypothesis that this vector autoregression analysis could influence is that there are possibly two channels through which Flight to Safety may be relevant to study investments and business cycles. Firstly, *Expectations channel*, which explains Flight to Safety shocks as being caused

Figure 2: FEVD (%) explained by FTS shocks



Notes: The k-step ahead Forecast error variance decomposition (FEVD %) explained by FTS shocks, in the 5-variable VAR, which is identified using Sign and Zero restrictions Identification Strategy 1. The 5 variables in the benchmark model are: TFP, Price of risk (Bond minus Equity price), Real rates, Surplus Ratio and Investments. In other iterations of the 5-variable model, 'Investment' is replaced with other macro variables of interest. The result of 'Investment' and only those variables that replace 'Investment' in the benchmark VAR are reported.

Figure 3: Historical Decomposition of Investments



Notes : Historical Decomposition of Investment in VAR model Y_t = [tfp$_t$, Bond-Equity$_t$, real rate$_t$, Surplus ratio$_t$, Investment$_t$]$'$, which is identified using Sign and Zero restrictions discussed in Strategy 1. X-axis label: years.

by a build-up of expectations of an impending deterioration in the economy or an expected downturn in the business cycle. Flight to Safety is thus only an indication of a negative total factor productivity shock expected to hit the economy. Therefore, rational, forward-looking households respond in the short run by moving investments from risky equities to safer bonds to safeguard their portfolio against future expected loss of income and wealth.

A similar approach is followed in news shocks driven business cycle literature [see Nam and Wang (2019), Beaudry, Nam, and Wang (2011), Beaudry and Portier (2006) and (2014)] which postulates that cyclical fluctuations emerge when economic agents update their expectations from news about future productivity.

Secondly, the *Speculative channel*, according to which investors and businesses that have an understanding of the economy, pre-empt others by taking speculative positions. A Flight to Safety shock then is an over-correction by speculators to disappointing economic news. If enough speculators, investors, customers, and entrepreneurs over-correct, they can engineer a crisis of its own. Put, as per the expectations channel, Flight to Safety shock is a response to the expected future state of the economy, whereas in line with the speculative channel, a Flight to Safety shock results from an optimistic bet on the economy that turned-sour in the current state. The technology used in the analysis in this chapter is neither sufficient to identify the role of expectations, nor is it the central objective of this study to identify such channels. Still, by looking at the VAR study's evidence, there is some inclination to favour the Expectations channel. Aligning the results with estimation from a theoretical DSGE model could enhance our understanding of these channels.

This chapter contributes to growing macro-finance literature by developing facts about the Flight to Safety mechanism and linking it with time-varying risk aversion and precautionary savings motive of agents/investors and financial intermediaries. The linkages between FTS mechanism and behavioural features related to investments have not been included even in the following literature, which is considered seminal on Flight of Safety. Vayanos (2004) provides a theoretical introduction to the FTS phenomenon in asset pricing literature. Cochrane (2016, 2017) presents a macro-finance model that links changes in investor excess consumption to Flight to Safety. Baele, Bekaert, Inghelbrecht, and Wei (2019) and Baur and Lucey (2009) document the incidence of Flight to Safety across major countries. And Boudry, Connolly, and Steiner (2019) provides impact of Flight to Safety on liquidity returns, revenues and valuation of the commercial real estate industry. The previous literature has also explored the Flight to Safety mechanism in a limited way. Two common themes stand out. First of all, it is to consider FTS as being generated through market imperfections or externalities. These have been explored in the form of liquidity constraints [He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014)], Knightian uncertainty (Caballero and Krishnamurthy, 2008), margin requirements of speculators (Brunnermeier and Pedersen, 2008), and intermediary balance sheets (Adrian, Boyarchenko, and Shachar, 2017). The second perspective is to consider FTS as a short term asset market phenomenon. The kernel-based approach discussed in Baele, Bekaert, Inghelbrecht, and Wei (2013) exemplifies this perspective. It measures the likelihood of observing an FTS event. Either through a threshold-based method that calculates how each trading day compares to the distribution of return differential between bond minus equity returns. Alternatively, measuring it by an ordinal index-based method ranks each trading day on how it complies with the weak and strong symptoms attributed to an FTS day. This chapter relies on a quarterly time series of equity index and government bond yields to identify Flight to Safety shocks. It stays away from extreme but for short duration only movements in volatility, asset prices, and other high-frequency variables. Working with high-frequency data (like Baele, Bekaert, Inghelbrecht, and Wei (2013)) would not have answered one of the primary purposes of this study, which is to evaluate the long-term impact of FTS. If an extreme flight of investment from stocks to bonds over one week reverses in another week, that would leave the aggregate investment allocation for the quarter as unchanged and, therefore, less relevant for our macroeconomic analysis. The Flight to Safety shocks identified in this chapter are robust to similar results from kernel-based methods of identifying such shocks. However, compared to other approaches, the vector autoregressions approach followed here has higher universal applicability.

This chapter pursues a novel approach to develop stylised facts about Flight to Safety. I use agnostic identification which follows from Uhlig (2005) and Arias, Rubio-Ramírez, and Waggoner (2018). The sign restrictions based identification, building on the work of Canova and Nicoló (2002), Faust (1998) and Uhlig (2005) restricts the signs of specific impulse responses in the structural VAR, and without undercutting scientific inquiry, it keeps them in line with tenable priors accepted in theory. This strategy contributes to the literature by imposing minimal sign-based restrictions on the structural VAR and not using the orthogonal ordering approach. The latter assumes some macro variables as sluggish to react to shocks. The identification in this chapter imposes no restrictions on the key business cycle variable of interest.

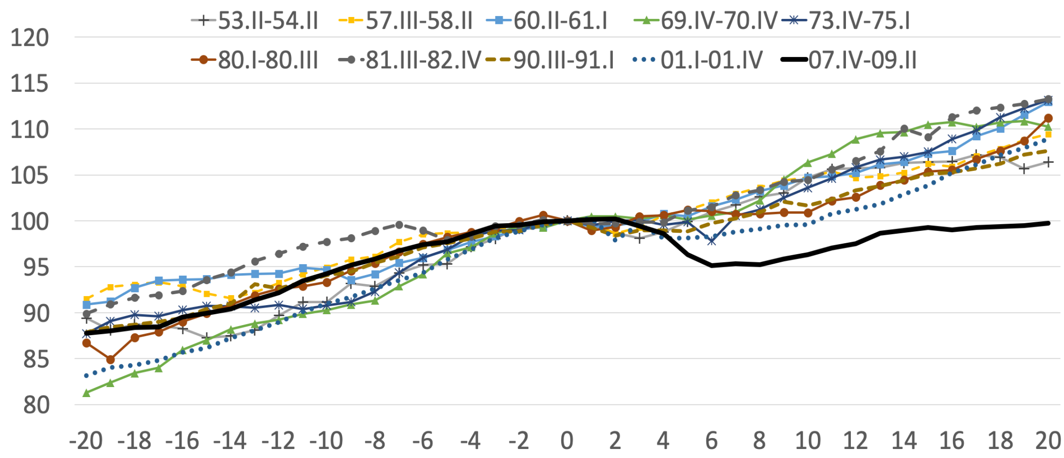
The success of an identification strategy depends on the plausibility of impulse responses it generates. This chapter's reasonable sign restrictions do not contradict with established results from DSGE models (Smets and Wouters, 2007). This impulse response-based identification strategy generates bounds on key variables of interest responses to structural shocks in the VAR. The identification strategy does not impose any sign restrictions on the key variables of interest, such as Output, Investment, Consumption, Hours, Unemployment, Labour productivity, Residential Investment, Non-Residential Investment, Capital Expenditure, R&D Expenditure, Consumer Prices, Government consumption and Expenditure, Prices of Investment goods in terms of Consumption goods, Consumer Sentiment, Capacity Utilisation, Vacancy rate, Participation rate, Foreign flows, and Wages. So in words of Uhlig (2005), the business cycle variable of interest remains agnostic to the identification. On the one hand, identifying FTS through S-VAR and sign restrictions differs from the existing approach to address this topic. On the other hand, this approach to study this phenomenon through vector autoregressions has a universal appeal.

The primary motivation for looking at the FTS phenomenon and obtaining its long term impact on the US macroeconomy comes from the unprecedented nature of the global financial crisis of 2007-08 and its long-lasting impact on consumption and investment data series. Compared to previous post-war recessions, the US's recovery following the global financial crisis has been muted and unprecedented for many quarters. Investment per capita in the US (as shown in Figure 4 on page 16), fell sharply after the Global financial crisis of 2008. Similarly, Consumption of Non-durable goods and services[2] was most distinctly impacted by the global financial crisis than any previous post-war recession. These series have been sluggish to return to its pre-crisis levels, as shown in the Figure 4 on page 16. During the global financial crisis, the performance was the worst performance of Investment, Consumption of non-durable and services, and many other macroeconomic aggregates in comparison to any post-war recession. The global financial crisis also dampened business sentiment (as shown in Figure 5 on page 17), but intriguingly, the impact was not so severely different from other previous recessions. Therefore sentiment alone cannot account for the significant decline in macroeconomic aggregate variables (esp. Investments) during the global financial crisis, and we have to look for alternate causes. This search for alternative explanations for the GFC was one of the chief motivations behind undertaking this study.

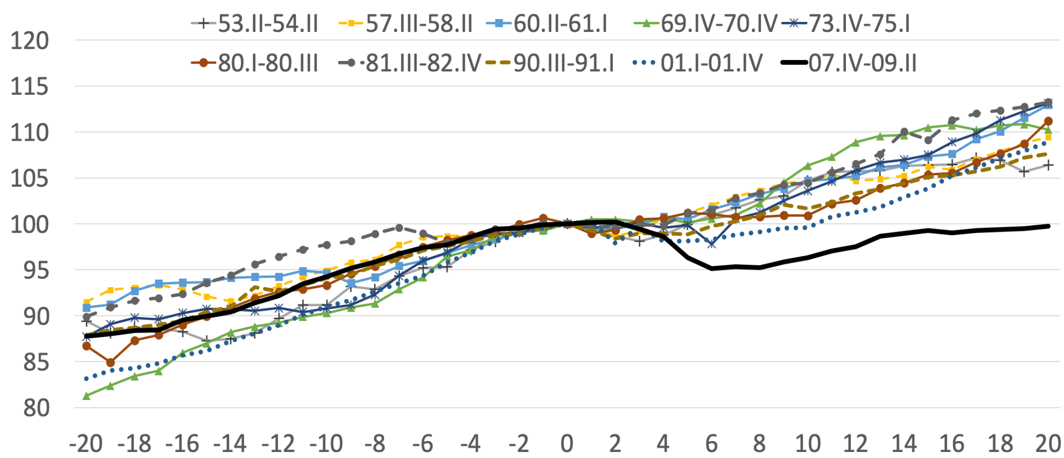
[2]For this chapter only, we can characterize this series as Consumption habits.

Figure 4: Global financial crisis and US recessions

(a) Private Investment per capita

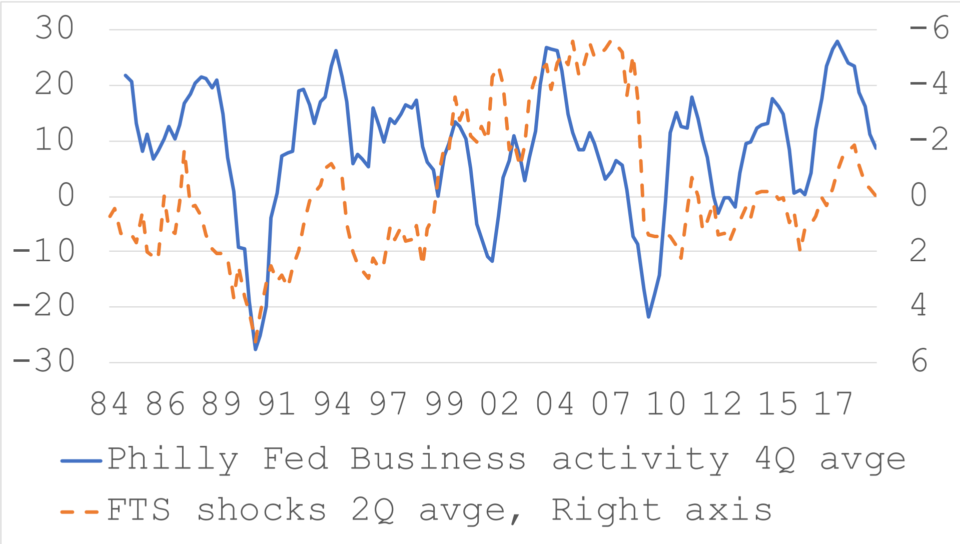


(b) Habits (Services and Non-Durables Consumption) per capita



Notes : Value at the peak of the each recession is indexed at 100, and corresponds to 0 on the X-axis, which denotes the time period in quarters pre and post the peak of a recession. The legend denotes peak to trough duration of a recession, for.eg. 07.IV-09.II is the peak to trough period 2007Q4-2009Q2 of the 2007-09 recession. Source: US FRED, NBER

Figure 5: Identified FTS shocks and Business outlook index



Notes: The figure shows Flight to Safety shocks (identified with restriction strategy 1) to a 5-variable benchmark VAR model, for Data: 1983:Q1 to 2019:Q3. The correlation between the two series is -52%. Two quarter average of identified FTS shocks (dashed, right inverted axis), and 4 quarter average of the Philadelphia Fed Manufacturing Business outlook survey (solid, left axis) are plotted.

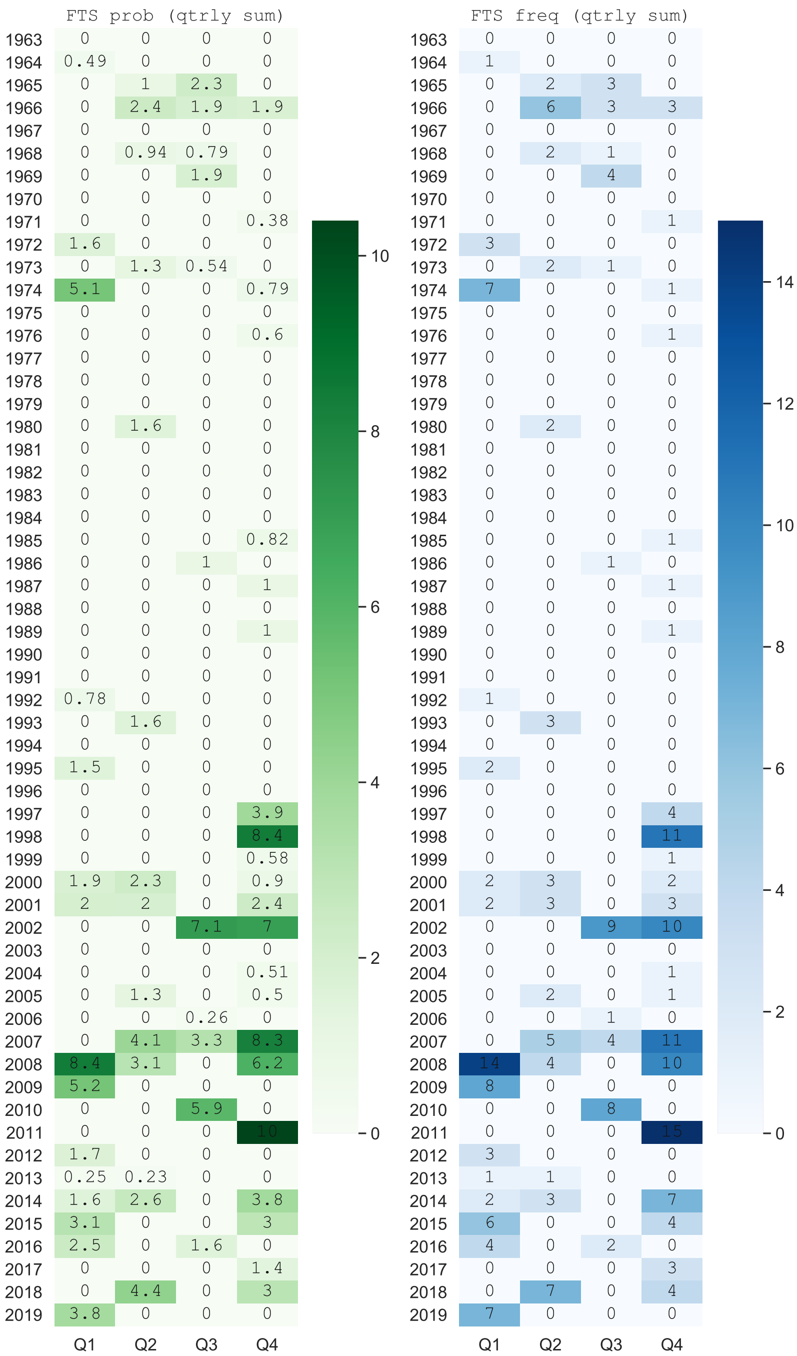
This unprecedented impact of the global financial crisis on the macroeconomic aggregates befits looking at explanations/mechanisms that could have been more relevant in the recent crisis than in any previous ones. Therefore, the search is for variables that had a somewhat more noticeable impact on the business cycle during the global financial crisis than the impact they had on the macroeconomic aggregate variables in any other post-war recession. Figure 6 on page 19 and results of Baele, Bekaert, Inghelbrecht, and Wei (2013) methods from Appendix B show that the incidence of Flight to Safety has increased in the last two decades, which makes it a phenomenon of significance in recent events and a likely differential that could explain the impact of the global financial crisis.

Let us look at some anecdotal evidence that the identified FTS shocks from the empirical study performed in this chapter, a 5-variable VAR with the sign and zero restrictions, capture the changes in US Business conditions expectations. The identified FTS shock series, as seen in Figure 5 on page 17, has a negative 52% correlation to US Philadelphia Fed Manufacturing Business Outlook Survey (MBOS). The latter is an index tracking the direction of change in overall business activity. This figure plots a cumulative sum of two-quarters of FTS shock on an inverted scale, i.e., the dips on the chart refer to Flight to Safety, and the peaks are a shock in the reverse direction or a Flight to Risk. The two series closely track each other; they slowly increase through the Dotcom period of the 90s, ending with a bust in 2001. The housing sector bubble build-up in the 2000s, and the recession of 2007-08 are also visible. Most importantly, the inverted cumulative FTS shock has a peak to trough drop of near eight percentage points during 2007. It marks the worst peak to trough for identified series in the tested period (1983 to 2019). However, the worst peak to trough drop of Business confidence series during 2007 was similar to the one in the late 80s crisis. Monetary easing in the 1990s and 2000s was able to restore business confidence. However, we notice that despite the unprecedented monetary policy response following the Lehman crisis, there is a lack of recovery in business confidence, and it did not return to its peak for nearly a decade. Therefore, reasons/factors that were not prevalent in the 1980s were the main reason behind the dip in consumer sentiment during the GFC. This supports our faith in the original expectation that the identified FTS shocks from our VAR exercise, which have been unprecedented in times preceding the GFC, capture the GFC's driving mechanism, which was an unprecedented post-war economic downturn.

This chapter takes a small step forward in emphasizing the Flight to Safety and changes in investors' risk aversion as variables of significance in the business cycle. It would be interesting to see, in future research, if the findings of this chapter are consistent with results from an estimated DSGE model or whether there is a need to impose any additional restrictions based on general equilibrium modeling to bolster this chapter's findings further.

The rest of the paper is structured as follows. The next section 2 makes a brief discussion of related literature. Section 3 describes the data. It is followed by a description of the benchmark 5 variable model's identifying assumptions in section 4. This section also discusses the theoretical and numerical algorithm for sign and zero restriction identification employed in this chapter. Section 5 discusses the results from empirical analysis, their impact on business cycle variables, the forecast-error variance, and brings to light the asymmetry between Flight to Safety and Flight to Risk shocks. Section 6 performs sensitivity exercise on the results. It also discusses the alternative identifications of Flight to Safety shocks and their significance in various periods. Section 7 discusses the identified FTS shocks with methods propounded in literature in explaining business cycle fluctuations while section 8 concludes.

Figure 6: Frequency and Likelihood of Flight to Safety days.



Notes: Heatmap for frequency (freq) and aggregate likelihood (prob) of Flight to Safety (FTS) days in each quarter from 1963 to 2019. FTS days are calculated by Ordinal index approach (see Appendix B.3), for $k = 1.25$. Aggregated likelihood or strength of FTS, for each quarter in the studied period is calculated by adding the likelihood for each FTS day during that period.

2 Literature review

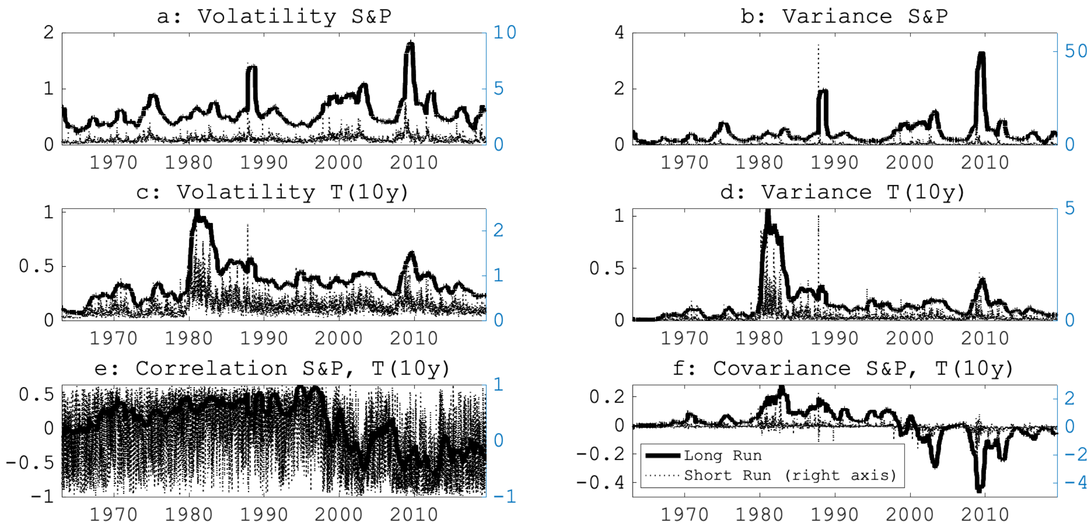
This section discusses both theoretical and empirical research related to Flight to Safety. In the wake of the global financial crisis, uncertainties about the growth and economic outlook have led to many pronounced episodes of negative correlation between returns on government bonds and stock returns. The returns on government bonds (safe assets) were positive, while the stock returns (risky asset) were negative. During such instances, there was also deterioration in market liquidity and an increase in volatility (See Figure 7 on page 21). It is such episodes that are commonly referred to as Flight to Safety (or FTS). However, the economic literature also uses FTS as an inclusive term for two other phenomena, *viz. Flight to Quality* (FTQ) and *Flight to Liquidity* (FTL), where the key difference between these two terms results from the underlying preference (whether for liquidity or quality) of investors that has motivated them to re-balance their portfolio from risky to safe assets.

Precautionary motives and risk aversion

A typical FTS episode is signified by a sudden increase in appetite for safe assets with respect to risky assets. The idea that during times of uncertainty, economic agents change their behaviour, by exhibiting caution towards excessive consumption and increase their savings, is quite old and one of the defining reasons for the study of macroeconomics. Agents that are uncertain about their future income and employment, exhibit precautionary behaviour to increase savings today to smooth out their consumption path and ameliorate the impact of realisation of a bad state in future. Modern understanding of the precautionary motives often refers to discussion in Keynes (1936), however there is an even earlier precedent in Marshall (1890), "The thriftlessness of early times was in great measure due to the want of security that those who made provision for the future would enjoy it".

Theoretical macro-finance literature [pioneered by Bernanke, Gertler, and Gilchrist (1996), Bernanke, Gertler, and Gilchrist (1999), and Kiyotaki and Moore (1997)], demonstrates the impact of small shocks on the macro economy. Persistent effects from these shocks can permanently damage agents' net worth through a drop in prices of assets they hold. Moreover, it feeds into a feedback loop where the fall in prices amplifies the initial mechanism and reduces agents' net worth even further.

Figure 7: Conditional volatility in financial markets



Notes: Long run and Short run (right axis, in all charts) conditional volatility, correlation and covariance for daily returns (%) of S&P 500 and US 10-year Treasury bonds. The long run variances are calculated by using a backward looking kernel of 250 days, whereas short run variances are calculated by backward looking kernel of 5 days. See Appendix B.1 for a detailed methodology.

A rise in precautionary motives and increased risk aversion reduces investment demand and fuels deflationary pressure, which can be self-fulfilling. As per Brunnermeier and Sannikov (2014) when prices drop in a crisis due to higher expected returns, agents hold on to cash for buying assets later at fire-sale prices, which elongates periods of low growth and asset misallocation.

The theoretical asset pricing literature on investor related Flight to Safety is pioneered by Vayanos (2004). In his model, fund managers face a funding constraint in the form of the likelihood of withdrawal of managed funds by individuals that are investing in these funds. The fund managers' funding constraint depends on the fund (i.e., whether it outperforms a threshold set by investors). This funding constraint also evolves endogenously on the level of market liquidity and volatility. During volatile times, there is an increase in probability with which the fund's performance could fall short of investors' threshold set. In volatile periods, this feature increases fund managers' risk aversion and leads to a preference for more liquid (FTL) and safer (FTS) assets.

Financial constraints based models in He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014), show that the amplification from small shocks grows for these financially constrained agents when their wealth is at a distance from the steady-state. When the endogenous risk is driven by financial constraints instead of being driven by fundamentals, it increases agents' precautionary savings motive. Precautionary demand and savings are shown to play an essential role in other industries as well. Empirically Kilian (2009) decomposes oil prices and addresses that from 1975-2007 precautionary demand shocks, which is uncertainty about future supplies, had an immediate and persistent impact on oil prices. Whereas during that period, the contribution to oil prices from disruptions due to supply shocks had been often short lived, and contribution from global demand shocks had been persistent but somewhat delayed.

Wealth preservation and liquidity preference are other two commonly studied motives for FTS. Boucher and Tokpavi (2019) study whether (high or low) bond yield environment affects the strength of these motivations. In their quantile regression model, an environment of low bond yields, expansionary monetary policy, and low inflation jeopardize the well-known diversification benefits of holding US treasury bonds. There is a decrease in the traditional Flight to Safety channel's strength, i.e., switching investments from equity to bond. It gets substituted by a pick up in the strength of Flight to Safety from equity to other safe-haven assets viz. Gold, Japanese Yen (JPY) and Swiss Franc (CHF).

The CAPM literature establishes FTS as the joint occurrence of higher economic uncertainty, low cash flows, high risk premium, high precautionary savings motive and low real rates. FTS episode in asset pricing literature results from the precautionary response of investors to changes in economic conditions. When uncertainty (quantity of risk) or stock market volatility increases, then the agents, investment managers, speculators in asset pricing models become more risk-averse and prefer safe and high-quality assets.

Liquidity, volatility and market externalities

There is a macro, asset pricing, and CAPM literature pattern that the Flight to Safety mechanism is linked with precautionary behaviour and changes in risk aversion of household/investor. But other theoretical studies have explored FTS in relation to speculation, liquidity, and market volatility. Acharya and Pedersen (2005) study the relation between liquidity shocks and adverse economic and financial episodes. Illiquid securities in their results have a higher sensitivity to market liquidity and market returns. Stocks with higher liquidity risk on average command an additional 1.1% risk premium.

Previously observed episodes of Flight to Quality, including Penn central transportation company default of 1970, Crash of 1987, Russian default, the Asian crisis, Bailout of LTCM, and events following attacks of 9/11 were not just instances of capital/liquidity shortages. These episodes also witnessed disengagement by investors from risky activities. In the words of Caballero and Krishnamurthy (2008), these were instances of Knightian uncertainty or immeasurable risk. Their model demonstrates that agents and intermediaries faced with an increase in Knightian uncertainty or liquidity shortages give more consideration to the worst possible outcomes. Such agents become self-protective and conservative in the allocation of risk capital, thus rendering capital markets inflexible. A resolution to this situation exists in the form of a massive policy involvement from the government acting as lender of last resort and transferring some of its collateral, trust, and liquidity to the distressed capital market (Caballero and Kurlat, 2009).

Speculators during FTS suffer from the destabilizing effect of margin requirements (Brunnermeier and Pedersen, 2008). When speculators' funding liquidity is tight and has higher margin requirements, they provide more liquidity for assets with low margin requirements (and are safer). This generates FTS and co-movement of risk premiums in capital markets. In Brunnermeier and Pedersen (2008), high market volatility creates a differential between the liquidity of safe and risky stocks. In other related studies, there is a deterioration of aggregate liquidity due to either lower net worth of intermediaries (Adrian and Shin, 2010), or effect of regulation on intermediary balance sheets (Adrian, Boyarchenko, and Shachar, 2017), or dynamic adverse selection (Guerrieri and Shimer, 2014). When combined with uncertainty averse behaviour of agents, any of these could lead to portfolio reallocation from risky to safe assets, or FTS.

The empirical literature mainly studies the FTS as a high-frequency event and focuses on its impact on returns, liquidity and volatility of the asset markets (Acharya, Pedersen, Philippon, and Richardson, 2016). The distinction between liquidity profile of corporate bonds impacts the way different bonds react to FTS (Acharya, Amihud, and Bharath, 2013). There is a notable reduction in illiquid or stress regimes' asset prices, particularly for less liquid assets. The prices for investment-grade US corporate bonds are less affected than those of speculative (junk) grade bonds. A similar effect is visible in stocks with low book-to-market value ratio.

Baur and Lucey (2009) find that FTS episodes are a regular occurrence in crisis periods and show contagion for eight developed countries that they study. FTS demonstrates the resilience and diversification benefits of financial markets for investors, as it shows that there is an asset class that can absorb excess capital in times of crisis. Markets lacking an FTS absorbing asset class suffer more significant losses and are less resilient in a crisis period. Using daily data for 23 countries, Baele, Bekaert, Inghelbrecht, and Wei (2013) further provide some stylized impact of FTS. FTS phenomenon coincides with an increase in the Volatility Index (VIX), a decrease in consumer sentiment, a higher preference for holding safe-haven assets (Gold) and currencies (Japanese Yen JPY, and Swiss Franc CHF), and a rise in the TED spread, which is the difference between the 3-month Treasury bill and the 3-month US dollar LIBOR. Boudry, Connolly, and Steiner (2019) provide the impact of FTS on high-frequency responses such as short-term liquidity and returns, and the low-frequency response variables such as long term revenues and valuation, of the commercial real estate industry. Brunnermeier and Nagel (2008) demonstrate that individual investors do not depict any portfolio reallocation towards more risky assets as their wealth increases; instead, they re-balance slowly following capital gains/losses. The regression of daily returns of Gold prices on stock and bond returns of UK, US, and German markets, in Baur and Lucey (2010) demonstrates that Gold has short-lived safe haven (safer asset) properties during extreme stock market events. Whereas in normal times, Gold is a hedge (uncorrelated) to stock markets.

Sign restrictions and expectations dynamics

Cochrane (2017) finds that changes in economic fundamentals lead to FTS, and it has a long-run impact on the asset valuations and macroeconomic variables. Despite that, there is no empirical study explaining the impact of FTS on short and long-term fundamentals of the economy. One possible reason for this could be the difficulty in separating the endogeneity of business cycles to FTS. Boucher and Tokpavi (2019), is a notable exception, as they find that the strength of FTS from stocks to bonds weakens as the interest rate on government bond maturities fall towards ZLB. They highlight the endogenous mechanism, which translates the state of the business cycle and the level of interest rates to the strength and likelihood of the FTS. In their analysis, during a low yield environment, the FTS from stock to bond is substituted by the FTS from stock to other safe-haven assets such as Gold and Swiss Franc. In comparison, this chapter aims to understand both the long and short-term impact of FTS on the macroeconomy, especially the short and long-term impact of FTS episodes on depressing private investments, including residential and non-residential investments, in the US economy.

The sign restrictions based identification used in this paper also complements with significant empirical work done using sign restrictions in identifying the impact of macroeconomic shocks in explaining the business cycles. Previous research has used sign restrictions to identify monetary policy shocks (Uhlig, 2005), government spending shocks (Mountford and Uhlig, 2009), financial shocks [Hristov, Hülsewig, and Wollmershäuser (2012), Gambetti and Musso (2017)], oil price shocks [Baumeister and Peersman (2013), Kilian and Murphy (2012)], technology shocks [Dedola and Neri (2007) and Peersman and Straub (2009)], uncertainty shocks (Bloom, 2014), changes in the volatility from monetary policy shocks (Theodoridis and Mumtaz, 2015), financial and uncertainty shocks (Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek, 2016), news shocks [Beaudry and Portier (2006), Barsky and E. R. Sims (2011), Beaudry and Portier (2014)], and mood swings [Beaudry, Nam, and Wang (2011), Nam and Wang (2019)].

Sign based identifying restrictions command an active space in empirical research and has kept pace with new techniques, such as using agnostic priors (Arias, Rubio-Ramírez, and Waggoner, 2018) and in combination with Bayesian FAVARs (Ahmadi and Uhlig, 2015). Sign restrictions have been useful in enhancing our understanding of macroeconomic shocks and their propagation, and this paper contributes to its growing arsenal.

A related view of this chapter's risk-driven business cycle hypothesis is the news-driven business cycle hypothesis (Beaudry and Portier, 2006), which posits that booms and bust cycles can arise from better or worse expectations about future fundamentals. According to the news-driven business cycles hypothesis, favourable news about future factor productivity can ignite a boom today via creating an incentive to accumulate and install new capital for future demand. In contrast, a less than expected realization of total factor productivity today could lead to bust even without any actual fall in total factor productivity or changes in fundamentals.

The empirical evidence supported in VAR based identification schemes in [Beaudry and Portier (2006) and Beaudry, Dupaigne, and Portier (2011)] backs this claim, and noise shocks, i.e., misinformation about future total factor productivity, are related to positive co-movement in macroeconomic aggregates observed in data. Jaimovich and Rebelo (2009) provides an alternate viewpoint that positive news may reduce the incentive to accumulate capital and instead favour an increase in utilization of capital. Increased capacity utilization in itself leads to a boom. However, the news-driven hypothesis is questioned under a different identification scheme (Barsky and E. R. Sims, 2011). The impact of noise shocks is similar to that of a standard DSGE model. A better than expected total factor productivity leads to an increase in consumption but a decline in output, hours, and investment. The VAR-based evidence of news based literature is criticized (Arias, Rubio-Ramírez, and Waggoner, 2018) for its non-fundamental, non-invertibility, the sensitivity of cointegration assumptions, and choice of variables in the system. If stock prices are not included in the system, the results do not confirm news shock driven business cycles.

This chapter proposes another view to this debate that it is not noise shocks to news about future total factor productivity. Instead, investor risk aversion shocks lead to booms and busts in the business cycles. The Flight to Safety shocks identified in this analysis lead expectation formation and TFP changes by much longer periods than postulated by either news shocks or uncertainty shocks. The macroeconomic theory-based identification employed in the benchmark analysis is robust to alterations in sign restrictions. The fact that other time series can account for the Flight to Safety phenomenon can also produce results comparable to the benchmark analysis, reassuring our faith in this analysis's results. The significant results are not entirely dependent on the inclusion of the singular price of risk series. In this manner, we avoid some criticism levied on the replicability of news shocks results with other series. Moreover, it appeals to the universality of the cyclical risk aversion phenomenon captured in Flight to Safety.

As global financial markets have grown increasingly more interconnected, the last couple of decades have seen FTS episodes (See figures 26 and 27 in Appendix B.3) occurring more frequently and commonly around the world. Baele, Bekaert, Inghelbrecht, and Wei (2013) report 2.7% FTS days in the US, and similar instances of FTS in 23 other countries.

Economic literature witnessed an increase of interest in the phenomenon of Flight to Safety. However, it is still fledgling, and its stylized facts are being developed. More importantly, there is a lack of understanding about how Flight to Safety shocks would work in the context of standard business cycle models. This chapter embarks on a step in this direction by attempting to identify Flight to Safety shocks and their business cycle impact.

Table 1: Data series used in VAR models

Series	Source Code	Definition
Output	GDP	Gross domestic product
Disp. Income	DPIC	Disposable Personal Income
Consumption	PCEC	Personal Consumption Expenditures
Durable	PCDG	PCEC: Durable Goods
Non-Durable	PCND	PCEC: Non durable Goods
Services	PCESV	PCEC: Services
Investment	GPDI	Gross Private Domestic Investment
Res Investment	PRFI	Private Res. Fixed investment
Non-Res Investment	PNFI	Private Non-Res. Fixed investment
Gov CI	GCE	Govt. Consumption Exp. & Gross Investment
Policy rate	FEDFUNDS	Effective Federal Funds Rate
CPI	CUSR0000SA0	Consumer prices - Urban
Participation	CIVPART	Labour force participation ratio
Vacancy rate	composite HWI	Help-Wanted Index*
Unemployment rate	UNEMP	Unemployment rate
Wages per hour	$\frac{\text{A576RC1}}{\text{TOTLQ}}$	$\frac{\text{Compensation}}{\text{Hours}}$ from Non-farm payrolls
Hours	NFBUS	PNFS (excl. nonprofit): Hours
Employees	NFBUS	PNFS (excl. nonprofit): Employees
TFP	dtfp_util	Utilisation-adj TFP#
TFP(EqDur)	dtfp_I _util	Utilisation-adj TFP Equipment and Durables#
Rel. px Cons to Equ	relativePrice	Rel. price Consumption to Equipment
Disp Inc / capita	A229RC0Q0-52SBEA	Disposable Income per capita
Capex	BOGZ1FA38-5050005Q	Capex Domestic non-fin. sectors
Capacity Util	TCU	Capacity Utilisation: Total industry
R&D expenditure	Y694RC1Q0-27SBEA	GDP: Research and Development
Foreign portfol. flows	Equity & Debt	Cumulative flows (+ inflow, - outflow)
Uncertainty	EPU	Economic policy Uncertainty§
Inv share	invShare	Equipment and Cons Dur share of output
Cons.Sentiment	UMCSENT	Consumer sentiment index
Term spread	DGS10, DGS1	10 year and 1 year Treasury bond
Corp bond spread	DBAA_AAA	Baa minus Aaa yield
Equity	˜GSPC	S&P 500 Index

Table 1 – continued from previous page

Series	Source Code	Definition
Deflator	DPCERD3Q0-86SBEA	PCEC (implicit price deflator)
Investment deflator	A006RD3Q0-86SBEA	GPDI deflator
Non Durables deflator	DNDGRD3Q0-86SBEA	Non-durables cons deflator
Durables deflator	DDURRD3Q0-86SBEA	Durables cons deflator
Services deflator	DSERRD3Q0-86SBEA	Services deflator

* Barnichon (2010) # Basu, Fernald, and Kimball (2006) § Baker, Bloom, and Davis (2016)

Sources: US FRED, BEA, BLS, IMF, Univ of Michigan, Datastream, FRBSF, Yahoo! Finance

3 Data

The source, purpose and definition of US data series that are considered in this empirical exercise are described in Table 1 on page 28, while Figure 28 on page 128 hosts the logarithmic time series plots of those data series.

This empirical study investigates the role of Flight to Safety or Flight to Risk shocks on the business cycle in the US from 1983 Q1 to 2019 Q3. The selected period includes the Great moderation period 1983-2007, which in the macroeconomic history witnessed a reduction in business cycle fluctuations in the developed world, esp. the US. The selection of the beginning date (the year 1983) for the data is made to ignore the impact of Oil shocks in the 1970s and the subsequent change in the Fed's monetary policy stance and communication strategy. The data also accounts for the global financial crisis period and the subsequent recovery period from 2009 to 2019.

The macro time series are obtained from US FRED database of the Federal

Reserve bank of St. Louis. Long-run macroeconomic data studied in this chapter (as produced in Table 1 on page 28) are the fundamental series that represent the long term macro-economic health of the US economy at any point in time. These are relevant to our research question of decoding the short and long-run impact of Flight to Safety shocks and Flight to Risk shocks on business cycles.

The empirical analysis is conducted through five variable vector autoregressions, of which the first four key variables are: Total factor productivity, Price of risk (bond minus stock prices), Real rates and Surplus ratio, and the fifth variable is the variable of interest. In the benchmark configuration the variable of interest is Investments. The variable of interest in subsequent iterations of the VAR model is changed to one of the following variables of interest: Hours (total), Output, Disposable Income, Term spread (or difference between 1-year and 10-year T-bill rate), Consumer prices Consumption (Total) and Consumption (only of Non-Durable goods and Services) which for this chapter only is also defined as Consumption Habits.

The series on total factor productivity (tfp) is adjusted for factor-utilisation using Fernald (2012), which follows Basu, Fernald, and Kimball (2006) and its updated version in (Basu, Fernald, Fisher, and Kimball, 2013) with the purpose to create quarterly growth-accounting database for the US business sectors[3] Utilization adjusted tfp series is a better approximation of true technological progress and has been previously used to identify the impact of news and expectations shocks (Jaimovich and Rebelo, 2009). This source also provides for the relative share of investment to output (invshare), the relative price of Consumption to equipment (pxceq), and the utilization adjusted tfp series for equipment and durables (TFP(EqDur)). All of which are considered in the sensitivity and discussion sections of this chapter.

The difference between log of bond prices and the log of equity prices is considered for series on Price of risk. An increase over time in the price of bond minus the price of equity signifies consumers' preference for safer asset vis-a-vis risky asset. Therefore identified positive shocks to this series are characterized as Flight to Safety shocks while identified adverse shocks to this series are Flight to Risk shocks.

There are two ways in which we can get the price of equity, or the risky asset,

[3]See Fernald's website, US Fred pages for data and comparable series of total factor productivity (Fernald 2012).

first, by merely using S&P 500 Composite Index. The data on the adjusted closing price of S&P 500 Composite Index is sourced from Yahoo! finance (series ˆGSPC). An alternate way to construct relative price for risk is to consider the 10-year P/E (price to earnings) ratio of S&P 500, which is available on Robert Schiller's webpage[4], and use it to deduce a ten years earnings yield for S&P 500. Consider this earning yield of S&P 500 as a yield to maturity of a 10-year S&P 500 index and use it to reverse engineer the price for Risky asset (S&P). US 10-year Treasury bond is considered a safe asset, and the data for 10-year nominal bond yield to maturity is sourced from US FRED database (series DGS10). The price for safe asset (10-year T-Bond) is reverse calculated from its yield to maturity.

By taking the difference of log series of nominal bond prices and the log of S&P prices (either through the index value or through 10-year price to earnings yield), a series for Price of risk can be generated. The former approach is considered in the benchmark VAR, and the sensitivity of results to the latter approach is discussed in later sections.

The ex-post real rate of return is given by the Federal funds (nominal) rate minus the US all Urban consumers (indexed 2012 = 100) inflation rate. The term spread is calculated by taking the difference between US 1-year and US 10-year yield, while corporate bond spread (Baa-Aaa) is sourced from Moody's. The surplus ratio is a series developed by considering One minus the ratio of Non-durable and Services consumption to total Consumption.

$$Surplus\ Ratio = \frac{Consumption_{Total} - Consumption_{NonDurables+Services}}{Consumption_{Total}} \tag{1}$$

Non-Durable and Services consumption has been considered by many as a measure of consumption habits and as a measure of permanent consumption [See for e.g. Justiniano, Primiceri, and Tambalotti (2010), Campbell and Cochrane (1999) and Cochrane (2017)]. Consumption habits series is developed by adding up personal consumption expenditure on non-durables (PCND) and personal consumption expenditure on services (PCESV) series from the BEA. The ratio of consumption habits to total consumption is a proportion of total consumption that satiates the household's habits or permanent level of consumption. One minus this ratio describes the proportion of consumption in excess of the habits or permanent consumption level. The literature on cyclical risk aversion considers the Surplus ratio as the key component of the household's utility (De Paoli and Zabczyk, 2013). The household feels a tighter pinch, or marginal utility of consumption

[4] http://www.econ.yale.edu/~shiller/data.htm

increases when the excess consumption gets closer to its long-term sustainable part [Cochrane (2017), De Paoli and Zabczyk (2013)]. The results of benchmark 5 VAR model are not sensitive to replacing the Surplus Ratio with Total Consumption.

The other series which replace the key variable of interest in the benchmark VAR are also taken from the US FRED database. The nominal series on Consumption is the real personal consumption expenditure (PCEC) from the Bureau of Economic Analysis (BEA). Durables consumption represents the personal consumption expenditure on Durable goods (PCDG) series of the BEA. Nominal output is measured by the Gross Domestic Product (GDP) of the BEA.

To further investigate the behaviour of the investments sector, this chapter also considers the following variables of interest: Durable goods consumption, Residential investment, Non-residential investment, Research and Development expenditure, Capital Expenditure, Price of Investment in terms of Price of Consumption and the Price of Investment and Consumption of Durable goods in terms of Price of Consumption habits (i.e., non-Durables consumption and services).

The nominal series on Investments is given by Gross private domestic investment (GPDI), the non-residential investment is represented by Private Nonresidential Fixed Investment (PNFI), and the series on Residential investment is Private Residential Fixed Investment (PRFI). The GDP Research and Development expenditure by BEA (Y694RC1Q027SBEA) is used for the R&D series. The above described nominal data series are converted into real data series by deflating using the Personal Consumption Expenditure (PCE) based implicit price deflator (DPCERD, indexed 2012=100). All the above variables are divided by population, which is reverse calculated from the Disposable income (DPI) and Disposable income per capita series (A229RC0Q052SBEA) of the BEA, to get respective real per-capita series that are used in the empirical analysis of this chapter. The relative price ratio of investment to consumption is calculated by using respective implicit price deflators (indexed 2012=100). Similarly, the ratio of the sum of deflators for investment and durables consumption to the sum of deflators for non-durables consumption and services gives the relative price of investment and durables.

The business cycle analysis also considers the insights of labour market variables: Hours (per worker), Output per labour (labour productivity), Labour force participation rate, Unemployment rate, Vacancy rate, and Vacancy to Unemployment ratio. Some other variables considered for robustness are consumer sentiment, capacity utilization, and Foreign portfolio flows.

Labour market indicators of Hours (total) and Hours per employee are taken from the Bureau of Labour Statistics (BLS). Total hours are measured by the hours of all non-farm businesses in the BLS data. Hours per employee are calculated by dividing total hours by the total non-farm business Sector employees. Real wages per hour are generated by deflating the Total Compensation of Employees (Wage and Salary Disbursements) personal income and outlays data (A576RC1) of BEA with the PCE deflator and dividing it by the total number of hours of employees on from non-farm payrolls, from BLS. Labour productivity is calculated by dividing real GDP with total hours. Labour force participation rate (CIVPART) and Unemployment rate series are from the BLS. The Government expenditure is Government consumption expenditure and gross investment (GCE1) data from the BEA and is deflated using the PCE implicit price deflator and divided by population to derive the Government expenditure per capita series of the empirical analysis. Quarterly data on Vacancy rate is from monthly Help-Wanted Index[5] (Barnichon, 2010).

Some other important sub-index series are considered in the empirical analysis. This includes the Total Industry Percent of Capacity Utilisation (TCU) series from the BEA, which is used for the Capacity Utilisation series. Capital expenditures for Domestic non-financial sectors from BEA (BOGZ1FA385050005Q) are used to develop the Capital Expenditure series. The economic policy uncertainty series constructed in (Baker, Bloom, and Davis, 2016) is used as a measure of policy uncertainty. Consumer surveys about consumer sentiment available for a long history from the University of Michigan are included in the analysis.

3.1 Downward trend

The Price of risk series as shown in Figure 28 on page 128 has a downward trend, which shows that the relative price of safe asset to risky asset has been falling. It was higher in the 70s and 80s than it was during the global financial crisis. For the Price of risk series we can say that there are many other factors, besides inflation that manifest in the price of bond and equities responsible for the downward trend. Investors adjust the bond yields[6] to account for various forms

[5]Constructed in 'Building a composite Help-Wanted Index' (Barnichon 2010).

[6] Price of a bond is an inversion of its yield. The analysis that is performed on yields can be translated into prices. In this chapter the nominal price of bond is measured by inverting

of embedded risks and in case of the long-dated bond, the term-premium[7]. Bond yields, therefore, adjust for the changes in safety premium, interest rate premium, reinvestment premium, duration premium, default premium, inflation premium, liquidity premium and event premium. The yields of long-dated (10 years) bond also adjust for the term-premium. All of which would impact the long-term bond yield[8] and the Price of risk series that we have included in this analysis.

Similarly the equity price is impacted by the underlying factors of dividend payments, mergers and acquisitions, reinvestment of capital, productivity increases, market power (domestic and global) and management changes. Besides factors that result in the time-varying nature of investor risk aversions such as increased globalisation and savings glut, they also contribute in uncertain ways to the Price of Risk series. A net effect of these over the years has been that the price of buying a real long term bond has been relatively falling to the real price of a unit

---

the 10 year bond yield, but I haven't come across any empirical work that works with bond prices by inverting bond yields. Shiller (2015) is an influential study on bond and equity return dynamics but it also uses yields (not prices) to develop a total return index for the long and short term bonds.

[7] Term premium is the amount by which the yield on a long bond is greater than the yield on a shorter dated bond. It is the premium that investors demand for holding a long term bond versus rolling over shorter term bonds for the same holding period. Ever since Fama and Bliss (1987) and Campbell and Shiller (1991), among others, found little evidence to support the Expectations Hypothesis which stated that the forward yield is market's expectation of short term rates in the future, it has become a widespread practise to decompose yields on long term bonds into two components: (i) expectations of future path of short-term interest rates and (ii) the term-premium. Term premium is deemed as a key ingredient in the optimal maturity structure of government debt (Greenwood et al. 2015) and an instrument through which monetary policy can influence long-term yields (Crump et al. 2016). Term-premia [See Kim and Wright (2005), Diebold et al. (2005) and Cohen et al. (2018)] are also the main driver of cross-sectional variation in yields, and contributed to co-movements between the US and the Euro area yields. The general equilibrium models of term-premium [Cox et al. (1985), or Lee (1995)], imply that the term-premium is a function of investors' attitudes toward risk. The term structure of interest rates varies according to market expectations and are very sensitive to the expected future path of growth, inflation, and monetary policy (Kliem at el. 2017), so a macroeconomic approach to understand it is warranted (Koop and Williams 2018).

[8] Common risk factors with respect to bond and bond fund investments, (as per FINRA https://www.finra.org/investors/learn-to-invest/types-investments/bonds/understanding-bond-risk) are as follows. Interest rate risk (or market risk, or holding -period risk) which is the possibility of an increase in interest rates during the holding period that would increase yields and lower the final selling price of the bond. Call risk (or reinvestment risk) which is the risk from an early repayment by the bond issuer. As interest rates fall, the bond issuer has an incentive to reissue at the prevailing low rates and repay the previously issued high interest bonds. Thus leaving the bond investor with no suitable reinvestment opportunities. Duration risk results from the sensitivity of bond prices to interest rate fluctuations. It is a non-linear function of bond's time to maturity. A shorter term bond has lower duration risk than longer dated bonds. Credit risk (or default risk) accounts for the possibility of default by the borrower. Inflation risk also impacts the price of the bond as rising inflation reduces the purchasing power of the returns on bond investments. Liquidity risk is the risk of not being able to find a buyer easily when required. Event risk from significant events such as war, trade-wars, mergers and acquisitions etc. is also a factor for valuing long term bonds.

of US equity index.

The benchmark 10 year treasury bond, whose price is used in the Price of risk series, is updated every year and so only the most liquid and relevant bonds are used. This avoids the changes in duration risk of the bond but it stays exposed to changes in interest rate risk, inflation risk and term premium. The equity index which is a market capitalisation based index is also regularly updated and that leads to a survivorship bias which means only the successful and large companies remain, while the failed ones are weeded out. The regular upkeep of the benchmark bond and equity series, keeps them relevant but exposes them to other biases. An ideal experiment would be to decompose each of the individual price effects of bond and equity prices and only compare them on the basis of safety premium. However in absence of such a natural data decomposition, the Price of risk series that we have considered in this chapter is a respectable alternative. The series could deviate from trend for the reasons that are peculiar to either bond or equity prices, but it would also deviate due to Flight to Safety and Flight to Risk. By way of the identification strategy employed in this chapter I present evidence that changes in individual risk aversion are a major source of such deviations.

3.2 Non-stationarity and Structural VAR

The variables considered in the VAR except unemployment rate, cpi and yield spreads, display a trend and are integrated of order one (see results in Table 2). The macro variables can be detrended by removing a deterministic trend or by first differencing before conducting OLS, otherwise one runs into the problems of spurious regressions, where the econometric procedure indicates relationship between two variables when none may exist. In that case single or joint hypothesis tests to examine the statistical significance of the coefficients and their standard errors are biased and the residuals violate the Gauss-Markov assumptions of no heteroscedastic and no auto-correlation. Therefore it is recommended especially while conducting unrestricted VAR and when working to devise point forecasts and causality that all of the components in the VAR have at least weak stationarity, that is they don't have time-varying first and second moments. But the spurious regression problem does not apply if variables are cointegrated[9] with one another.

[9]Two variables are said to be cointegrated if they are each unit root processes, but if a linear combination of them is stationary.

In such a case first differencing is not appropriate[10]. C. A. Sims (1980b), J. Stock, C. A. Sims, and Watson (1990) and Luetkepohl (2011) and others[11] have suggested that a way to avoid the problems of spurious regressions without first differencing is to obtain the structural VAR with higher number of lags, and that the forecast errors, historical decomposition, impulses responses and Granger causality based results are valid even for integrated representations. Therefore the structural analysis employed in this chapter avoids spurious regression by using 4-lags, imposing sign based restrictions and developing robust standard errors. Alternatively if the variables are co-integrated the Vector-error correction mechanism as presented in EC-VAR of Bansal et al. (2007, 2011) could be followed. They demonstrate that as cash-flow and consumption series are cointegrated, an error correction VAR describes a completely different optimal portfolio allocation, in particular for long term horizon, than a commonly used VAR approach. The return betas from their EC-VAR account for cross-sectional variation in equity returns, which is not the case if cointegration is ignored.

The next challenge is to devise an identification scheme to overcome the endogeneity in macroeconomic variables and other shocks that generate FTS behaviour. We answer these questions by isolating the business cycle and monetary policy shocks and only considering the FTS shocks that are orthogonal.

[10] Chris Brooks in his (2019) textbook Introductory Econometrics for Finance says, ".....many proponents of the VAR approach recommend that differencing to induce stationarity should not be done. They would argue that the purpose of VAR estimation is purely to examine the relationships between the variables, and that differencing will throw information on any long-run relationships between the series away" .

[11] Eric Sims proposes, "Differencing often feels like the right thing to do, but can result in serious mis-specifications if variables are cointegrated. Estimating in levels (provided there are lags of the dependent variable on the right hand side, which takes care of the spurious regression problem) is always safer" . Source: Eric sims' lecture notes https://www3.nd.edu/~esims1/time_series_notes_sp13.pdf.

Table 2: Unit root test results of various series

	Test Statistic	p-value	#Lags	#Obs	Critical values 1%	5%	10%
Util-Adj TFP	-0.801	0.819	0	146	-3.476	-2.882	-2.577
Price of risk	-1.204	0.672	3	143	-3.477	-2.882	-2.578
Real rate(%)	-2.086	0.25	11	135	-3.48	-2.883	-2.578
Consumption	-1.261	0.647	6	140	-3.478	-2.882	-2.578
Hours	-1.251	0.651	5	141	-3.478	-2.882	-2.578
Output	-1.22	0.665	2	144	-3.477	-2.882	-2.578
Investment	-1.967	0.301	2	144	-3.477	-2.882	-2.578
Cons (NDur+Svc)	-1.119	0.708	3	143	-3.477	-2.882	-2.578
Hrs per emp	-1.417	0.574	4	142	-3.477	-2.882	-2.578
Outp per Emp	-0.493	0.893	2	144	-3.477	-2.882	-2.578
CPI	-4.209	0.001*	0	146	-3.476	-2.882	-2.577
Surplus ratio	-0.877	0.795	3	143	-3.477	-2.882	-2.578
Participation rate(%)	-1.515	0.526	10	136	-3.479	-2.883	-2.578
Unemployment rate(%)	-2.762	0.064*	9	137	-3.479	-2.883	-2.578
Disp Income	-1.557	0.505	2	144	-3.477	-2.882	-2.578
Inv + Durables Cons	-1.472	0.547	3	143	-3.477	-2.882	-2.578
Rel.Px Inv	-3.711	0.004*	0	146	-3.476	-2.882	-2.577
Rel.Px Inv+DurC	-1.233	0.659	1	145	-3.476	-2.882	-2.578
Res Investment	-2.855	0.051*	5	141	-3.478	-2.882	-2.578
Non-Res Investment	-1.75	0.406	2	144	-3.477	-2.882	-2.578
Gov. Expenditure	-1.727	0.417	4	142	-3.477	-2.882	-2.578
R & D	-0.672	0.854	2	144	-3.477	-2.882	-2.578
Capex	-1.168	0.687	4	142	-3.477	-2.882	-2.578
1y-10y spread(%)	-3.58	0.006*	3	143	-3.477	-2.882	-2.578
Corp bond spread(%)	-4.744	0*	1	145	-3.476	-2.882	-2.578
Util-Adj TFP(Eq.Dur)	0.025	0.961	4	142	-3.477	-2.882	-2.578
Equity px	-1.632	0.467	1	145	-3.476	-2.882	-2.578
Bonds px	-3.006	0.034	10	136	-3.479	-2.883	-2.578
TR 10y-earn px	-3.352	0.013*	7	139	-3.478	-2.883	-2.578
10y-Cape px	-3.489	0.008*	3	143	-3.477	-2.882	-2.578
CAPE	-2.72	0.071*	1	145	-3.476	-2.882	-2.578
LT 10y-earn px$^{\#}$	-1.527	0.520	1	114	-3.489	-2.887	-2.580

Notes: ADF unit root test results for data series used in S-VAR. The null hypothesis of the test is, H_0 : The series has Unit root.* indicates results that are significant at 90%. $^{\#}$ series is available for period 1983-2011, all other results are for 1983-2019. Maximum 12 lags are considered for each series. #Lags describes the lag order which gives the best result to reject the Null hypothesis. #Obs is the number of observations left after accounting for lags.

4 Empirical analysis

This section describes the sign restrictions methodology that is adopted in this chapter to identify Flight to Safety shocks in the US. Sign and zero restrictions are derived from Uhlig's agnostic identification (Uhlig, 2005) and the methodology below is also supported by additional derivations presented in Appendix A. After describing the identification methodology, the section also presents the identifying assumptions and the theoretical rationale behind choosing them.

4.1 Methodology for identifying Flight to Safety shocks

The reduced form VAR and Uhlig's agnostic identification: Consider a VAR model in reduced form as in Uhlig (2005)

$$\boldsymbol{Y_t} = c_t + \sum_{k=1}^{p} \boldsymbol{B}_{(k)} \boldsymbol{Y_{t-k}} + \boldsymbol{u_t} \tag{2}$$

where $\boldsymbol{Y_t}$ is an m x 1 vector of endogenous variables, at date $t = 1, ...T$, $\boldsymbol{B}_{(k)}$ are reduced-form square coefficient matrices of size m x m and $\boldsymbol{u_t}$ is m x 1 one-step prediction error with m x m variance-covariance matrix $\boldsymbol{\Sigma}_u$. This reduced form VAR has a moving-average representation,

$$\boldsymbol{Y_t} = c_t + \sum_{h=0}^{\infty} \boldsymbol{\Phi}_{(h)} \boldsymbol{u_{t-h}} \tag{3}$$

where $\boldsymbol{\Phi_{(0)}} = I_m$. For simplification we can ignore the c_t term which comprises of intercept and/or time trend. This is mostly an agreeable representation of the reduced form VAR. The challenge in identification lies on how we decompose the forecast error $\boldsymbol{u_t}$. If we assume that there are m fundamental, mutually independent innovations, i.e. one shock for each endogenous variable, which are normalised to be of variance 1. They can be represented by a m x 1 vector v such that

$$E[vv'] = \Sigma_v = I_m. \tag{4}$$

The identification problem is then restricted to finding a linear mapping between reduced form innovations $\boldsymbol{u_t}$ and structural shocks v_t. The mapping is represented by an unknown matrix $\boldsymbol{A}$ such that

$$\boldsymbol{u_t} = \boldsymbol{A} v_t \tag{5}$$

The jth column of $\boldsymbol{A}$ represents the impact on all variables of VAR of the jth fundamental innovation. However identifying such an $\boldsymbol{A}$ matrix is not straightforward as the variance-covariance matrix of $\boldsymbol{u_t}$ which now can be written as

$$\boldsymbol{\Sigma}_u = E[\boldsymbol{uu'}] = \boldsymbol{A}E[vv']\boldsymbol{A'} = \boldsymbol{AA'} \tag{6}$$

also holds true for $\tilde{\boldsymbol{A}}$ which is any arbitrary orthogonalisation of Σ_v . For instance consider a Cholesky decomposition of $\Sigma_v = \tilde{\boldsymbol{A}}\tilde{\boldsymbol{A}}'$ and some orthonormal matrix P such that

$$\boldsymbol{A} = \tilde{\boldsymbol{A}}P \tag{7}$$

$$\boldsymbol{AA'} = \tilde{\boldsymbol{A}}PP'\tilde{\boldsymbol{A}}' = \tilde{\boldsymbol{A}}\tilde{\boldsymbol{A}}' \tag{8}$$

Therefore the identification of the structural shocks v_t requires us to pin down the orthonormal matrix P, which means there are another $m(m-1)/2$ restrictions required to achieve this identification. Commonly used procedures in this identification are recursive ordering of variables (C. A. Sims, 1986), breakup of components into transitory or permanent (Blanchard and Quah, 1989), structural relations between fundamental innovations and prediction errors (Bernanke and Mihov, 1998), and sign restrictions [Uhlig (2005) and Mountford and Uhlig (2009)]. I use Uhlig (2005) sign-restriction based agnostic identification method to find the effects of FTS on the economy. A clear advantage of the approach is that sign-restriction limits identification exercise to only k shocks of interest, and the other $m-k$ fundamental innovations can be ignored. By not imposing any sign restrictions on the response of variables of interest, the procedure remains 'agnostic' (in the manner of Uhlig, 2005) with regards to these variables and can be used in finding the effect of shocks on such variables. Following from the equations (3) to (8) we can deduce the structural VAR in moving average form as

$$\boldsymbol{Y_t} = c_t + \sum_{h=0}^{\infty} \boldsymbol{\Psi_{(h)}} v_{t-h} \tag{9}$$

where $\boldsymbol{\Psi}_{(h)} = \boldsymbol{B}_{(h)}P$, $\boldsymbol{B}_{(h)} = \boldsymbol{\Phi}_{(h)}\tilde{A}$ and v_{t-h} are the structural shocks. The impulse response of jth shock at horizon $h \in h^-, ..., h^+$ is given by the jth column $\boldsymbol{\Psi}^j_{(h)}$ of matrix $\boldsymbol{\Psi}_{(h)}$:

$$\boldsymbol{\Psi}^j_{(h)} = \boldsymbol{B}_{(h)}p^j \tag{10}$$

where p^j is the jth column of P. The response of the ith element of the system is thus given by the ith element on the impulse response vector

$$\boldsymbol{\Psi}^{i,j}_{(h)} = \boldsymbol{B}^{i,}_{(h)}p^j \tag{11}$$

$\boldsymbol{B}^{i,}_{(h)}$ is the ith row of $\boldsymbol{B}_{(h)}$ and p^j is the jth column of P. Thus sign and zero restrictions can be applied to response $\boldsymbol{\Psi}^{i,j}_{(h)}$ for some horizons h to identify any jth structural shock. It follows from Uhlig (2005) that the problem comes down to identifying the unit vector p^j which comes closest to meeting the sign and zero restrictions (See Appendix A).

The identification can be achieved by either selecting from Markov chain Monte carlo (MCMC) simulation a certain number of impulse responses that meet our pre-determined sign restrictions or by choosing a Penalty (or criterion) function $\Theta(p)$ which increases in the size of violation by impulse response to the selected sign and zero restrictions. For ease of notation I am dropping the j superscript in the equations that follow from here on. As discussed in Mountford and Uhlig (2009), in the Penalty function approach, selecting between sign restrictions then becomes a minimisation problem that solves,

$$p^* = \underset{p}{argmin}\ \Theta(p) \text{ s.t. } p'p = 1, \tag{12}$$

for the Penalty function,

$$\Theta(p) = \sum_{i \in i^+} \sum_{h=h^-}^{h^+} f\left(-\frac{\boldsymbol{B}^{i,}_{(h)} p^j}{\sigma_i}\right) + \sum_{i \in i^-} \sum_{h=h^-}^{h^+} f\left(\frac{\boldsymbol{B}^{i,}_{(h)} p^j}{\sigma_i}\right) \tag{13}$$

where i^+ is the set of variables whose impulse responses $\boldsymbol{B}^{i,}_{(h)} p^j$ are set to be positive and i^- is the set of variables whose impulse responses are set to be negative for the horizon $h \in h^-, ..., h^+$. Any zero restrictions on impact of the variable ordered zth in the VAR system, can be included in the minimisation problem by adding an additional constraint on the unit vector p as:

$$p^* = \underset{p}{argmin}\ \Theta(p) \text{ s.t. } p'p = 1 \text{ and } R_{zero} p = 0 \tag{14}$$

where R_{zero} is zth row of $\boldsymbol{B}_{(0)}$, i.e. $R_{zero} = \boldsymbol{B}^{z,}_{(0)}$. The minimisation is solved in Matlab using Simplex and inbuilt methods, and the estimation is conducted using Bayesian procedures as in Uhlig (2005).

The algorithm for both MCMC and Penalty based methods is thus given by:

1. Draw from Normal-Wishart prior.

2.a. For a given draw either solve (14) to get a candidate solution for p^* , or

2.b. Apply the stereographic inversion on the candidate solution to solve other constraints, i.e. unit length and meeting Zero restrictions.

3. Obtain statistical inference on the basis of draws that solve step 2.

Table 3: Identification restrictions in S-VAR

variables / *shocks*	TFP	Price of Risk	Real rate	Surplus ratio	Variable of interest
Strategy 1					
Productivity	+	.	−	+	.
Flight to safety	0	+	+	−	.
Monetary policy	0	.	+	−	.
Demand	.	.	.	.	.
Residual	.	.	.	.	.
Strategy 2					
Productivity	+	.	−	+	.
Flight to safety	0	+	+	0	.
Monetary policy	0	.	+	0	.
Demand	.	.	.	.	.
Residual	.	.	.	.	.
Strategy 3					
Productivity	+	.	−	+	.
Flight to safety	0	+	.	0	.
Monetary policy	0	.	+	0	.
Demand	.	.	.	.	.
Residual	.	.	.	.	.

Notes: The benchmark VAR has 5 variables: TFP, Price of risk (which is Bond price minus Equity price), Real rate, Surplus ratio (which is One minus the ratio of Consumption of services and Non-durables to Total consumption), and a variable of interest which in the benchmark case is Investments but is replaced in different iterations by other business cycle variables for e.g. Output, Consumption, Hours, CPI etc. On impact of the respective shock, + means the variable is restricted to be positive and − means that the variable is restricted to be negative for the impact horizon. The impact horizon is shock period plus one more period. Symbol 0 signifies a zero restriction when the response variable is restricted to not respond to the shock contemporaneously, and Dots . signify that the impact response of that variable is left unrestricted.

4.2 Sign and Zero restrictions based identification

The benchmark 5-variable VAR model consists of: Utilisation-adjusted Total factor productivity, Price of risk, Real rate, Surplus ratio and the variable of interest which in the benchmark configuration is Investments. In other iterations of the model the variable of interest is replaced by: Hours, Output, Consumption, Disposable income, Term spread between 1-year and 10-year T-Bill rate, CPI and Habits. Residential investments, Non-residential Investments, Disposable income, Wages (per hour), consumption of non-durables and services, Foreign portfolio flows, Government expenditure, Labour productivity. The structural model is given by:

$$\boldsymbol{Y_t} = c_t + \boldsymbol{B}_{(0)} p v_t + \boldsymbol{B}_{(1)} p v_{t-1} + ... + \boldsymbol{B}_{(\infty)} p v_{t-\infty} \tag{15}$$

where

$$\boldsymbol{Y_t} \quad = \quad \begin{bmatrix} \text{TFP,} \\ \text{Price of risk,} \\ \text{Real rate,} \\ \text{Surplus ratio,} \\ \text{Investment} \end{bmatrix} \tag{16}$$

and

$$v_t \quad = \quad \begin{bmatrix} \text{TFP shock,} \\ \text{FTS shock,} \\ \text{Policy shock,} \\ \text{Demand shock,} \\ \text{Residual shock} \end{bmatrix} \tag{17}$$

Three different identification strategies are adopted (See Table 3 on page 41) for considering impact, impulse response restrictions from FTS shock on the first 3 or 4 variables of the benchmark 5 variable VAR. The impulse responses from the 5th variable or the variable of interest in all strategies are left unrestricted. In this manner, the impact analysis is agnostic to the effect on the variable of interest. The identification strategies (in Table 3) are a set of sign and zero restrictions that are supported by theoretical models of the business cycles and by observations from data.

A prominent model that has been used in deriving sign restrictions in this chapter is the NK (New Keynesian) or NNS (New Neoclassical synthesis) Smets and Wouters (2007) model that is consistent with the balanced steady state growth path and is estimated by them using Bayesian methods. Their model has 7 orthogonal structural shocks in: total factor productivity, risk premium shocks, investment technology shocks, wage shocks, price markup shocks, exogenous spending (policy) shocks, and monetary policy shocks. It also incorporates many relevant policy analysis features, such as labour augmented technological progress, investment adjustment costs, variable capacity utilization, and real rigidity in intermediate goods and labor markets.

Several other interesting features of the Smets and Wouters (2007) model are as follows. Household chooses over consumption and labour effort. Labour is differentiated by a union, which gives monopoly power over determination of wages, which are Calvo-style sticky. Consumption habits are exogenous. Households make decisions to rent and accumulate capital based on the rental rate and capital adjustment costs. Firms decide on producing differentiated products and set prices based on present and expected marginal costs (wages and rental rate of capital), and past and expected inflation. Wages depend on past wages and future inflation. The medium-scale of this model, its micro-theoretic foundations and relevance of the variables it considers with the business cycle phenomenon, all together make it a standard workhorse model of monetary policy analysis and a reliable resource to base the identifying restrictions of the empirical study of this chapter.

The results of Smets and Wouters (2007) are consistent with the great moderation period 1984 to 2004 and demonstrate a fall in the volatility of shocks (related to total factor productivity, monetary policy, and price markup), the volatility of output growth and inflation, and the sensitivity of response of output variables to monetary policy shocks. They also show that during the great moderation, the monetary policy response to output changes has slowed. The reaction of policy to inflation has slightly increased, but the output gap's reaction has reduced by half. The sensitivity of their results to investment adjustment costs and consumption habits is high. Investment shocks result in the hump-shaped responses in output, hours, inflation, and interest rates.

The sign restrictions in this paper are based on the key results of Smets and Wouters (2007). In particular that technology shocks lead to a fall in nominal and real interest rates. However, for the monetary policy reaction function that they estimate, this fall is not sufficient to prevent a drop in inflation and an opening of the output gap. Risk premium shocks result in a fall in output, hours, and an increase in the real interest rate. Furthermore, monetary policy shocks lead to an increase in interest rate, real interest rate but decrease output, inflation, and hours. The sign restrictions are applied for a horizon of shock period and the next period, while the zero restrictions are applied for the shock period itself. These restrictions are represented in the $\boldsymbol{B}_{(0)}$ and $\boldsymbol{B}_{(1)}$ matrices, which are discussed next for the three different identification strategies.

4.2.1 Identification strategy 1

Identification strategy 1 (See Table 3 on page 41), applies zero impact restriction on TFP from monetary policy shock and Flight to Safety shock. Recall, that the ordering of the 5 variable VAR in benchmark configuration is: TFP, Price of risk, Real rate, Surplus ratio and Investment. Therefore on applying the zero restrictions the impact matrix $\boldsymbol{B}_{(0)}$ becomes

$$\boldsymbol{B}_{(0)} = \begin{bmatrix} . & 0 & 0 & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{bmatrix} \tag{18}$$

where dots (.) symbolise entries that remain unrestricted. On including sign restrictions given in Identification strategy 1 (see Table 3 on page 41) the $\boldsymbol{B}_{(0)}$ and $\boldsymbol{B}_{(1)}$ matrix are modified to

$$\boldsymbol{B}_{(0)} = \begin{bmatrix} + & 0 & 0 & . & . \\ . & + & . & . & . \\ - & + & + & . & . \\ + & - & - & . & . \\ . & . & . & . & . \end{bmatrix} \quad \text{and} \quad \boldsymbol{B}_{(1)} = \begin{bmatrix} + & . & . & . & . \\ . & + & . & . & . \\ - & + & + & . & . \\ + & - & - & . & . \\ . & . & . & . & . \end{bmatrix} \tag{19}$$

The sign restrictions in 5 variable VAR are implemented for a maximum horizon of one period after the shock, i.e. the restrictions are valid for the shock period and one period after. Any zero restrictions are imposed only on the impact period.

Identification strategy 1: restrictions to TFP shock In the 5 variable benchmark VAR model, Identification strategy 1 imposes negative sign restrictions from TFP shock (the first shock in VAR) on Real rates (the third variable in VAR) and imposes a positive restriction on Surplus ratio (the fourth variable in VAR). In models of business cycle, an increase in technological progress is expected to increase the household's desire for consumption and leisure. If we assume that consumption habits are slow to change, then it follows that an increase in household's discretionary consumption would raise the surplus consumption and the surplus ratio. However, the impact of real rates from a TFP shock is not that unambiguous. A positive TFP shock leads to decrease in real interest rate. This is consistent with the logic of standard Euler equation, where the current period real interest rates is inversely related to current consumption. For the policy maker with a dual mandate of price and output stability, in standard forward looking 3-equation New Keynesian (NK) model[12], it is optimal to consistently set interest rates equal to natural rate of interest. Therefore a TFP shock in models of price-rigidity warrants a cut in real rates to keep the output gap closed.

The literature based evidence points to a fall in natural rate of interest with increases in total factor productivity (Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez, 2017). But this causality is believed to run both ways, and low real rate through its effect on resource allocation affects TFP growth that drives natural rate lower (Cette, Fernald, and Mojon, 2016). Following from the work of Smets and Wouters (2007), in the identification strategy 1 I choose to keep the response of Real rates as negative on impact from the positive TFP shock. Results from Smets and Wouters (2007) demonstrate that both nominal interest rates and real rates fall on impact from a TFP shock, but by not enough to avoid a fall in prices.

Identification strategy 1: restrictions to FTS shock The impact from FTS shock is considered as orthogonal to the TFP shock and is included in the VAR through a zero restriction of the TFP (first variable in VAR) to FTS shock (second shock in VAR). If we cannot control for the state of business cycle (TFP shocks), then there could be confusion whether the increase in price of the safe asset is due to FTS or from a TFP linked economic downturn. The news shocks literature [Barsky and E. R. Sims (2009) and (2011), Beaudry and Portier (2005) and (2006)] also chooses some form of zero restriction on TFP from news/sentiment shocks.

[12]The forward looking 3-equation NK model (Galí, 2015) is given by:
the IS relation: $y_t = E_t[y_{t+1}] - \frac{1}{\theta}\left(i_t - E_t[\pi_{t+1}] + u_t^{IS}\right)$, $\theta > 0$
the Philips curve: $\pi_t = \beta E_t[\pi_{t+1}] + \kappa\left(y_t - y_t^n\right)$, $0 < \beta < 1$
and the policy rule: $i_t = r_t^n + \phi_\pi \pi_t + \phi_y \tilde{y}_t$, $\kappa > 0$
where u_t^{IS} is an AR(1) shock process, y^n is the flexible price level output, r^n is the natural rate that prevails flexible prices, and $\tilde{y} = y - y^n$.

Flight to Safety by definition is a phenomenon when capital moves away from risky assets to safer assets. Therefore on impact from a positive FTS shock the Price of risk (the second variable of the benchmark VAR), which is difference between Bond price and Equity price, is restricted with a positive sign restriction. Favourable (or positive) news shocks, in some TFP related news shock literature (Gambetti and Musso, 2017) are also linked to a fall in nominal rates after the 1980s. If we assume that FTS episodes are linked with pessimistic news about future TFP, then similar restrictions that are advocated on Real rates from a negative TFP news shock can be placed for identifying FTS shocks. Real rates responses are therefore restricted to be positive on impact from FTS shock. On impact of a Flight to Safety shock agents look to save for precautionary reasons and therefore their surplus consumption would reduce. This provides us with the third restriction which is a negative response of surplus ratio (the fourth variable in benchmark VAR) on impact of a positive FTS shock. This is also consistent with the results from Smets and Wouters (2007). That model has shocks to risk premium such that an increase in the premia leads to fall in variables of business cycle activity, such as hours and output and leads to an increase in the real interest rates. An increase in risk-premia does not translate one-to-one into preference for safety that is a hallmark of FTS. However, a risk premium shock leads to increase in expected rate of return from risky assets and a fall in their prices. As long as the shift in risk premium after the shock, is not uniform across the whole spectrum of investments (of range least to highest risk), it can be safely argued that the price gap between most risky and least risky investment widens after the risk premium shock and use of the results from Smets and Wouters (2007) is justified.

Identification strategy 1: restrictions to Policy shock To distinguish monetary policy (MP) shock from TFP shock, a zero restriction is placed on the response of TFP series (first variable in VAR) to monetary policy shock (third shock in VAR). This is a commonly used restriction in identifying structural monetary shocks in TFP and news shock literature (Beaudry, Nam, and Wang, 2011). No restrictions from the policy shock are placed on the Price of risk (second series in VAR). A positive monetary policy surprise will lead to an increase in nominal rates and fall in inflation expectations, therefore the Real rate responses (third variable in VAR) are sign restricted to be positive. In Smets and Wouters (2007) monetary policy shock leads to increase in interest rate, real interest rate, and decrease in inflation. Structural model based evidence, including Smets and Wouters (2007) supports the view that positive monetary policy surprises negatively impact consumption and surplus consumption and other business cycle variables including hours and output, and so the response of surplus ratio (fourth series in VAR) to positive monetary policy shock is sign restricted to be negative.

The shock to fourth variable (surplus ratio) which is a Demand shock is not strictly identified in either of the identification strategies 1, 2, and 3. Therefore no restrictions are imposed on the response of any variables in the VAR from demand shocks that impact the Surplus ratio. There may be a case to include an additional restriction that positive demand shocks lead to increase in Surplus ratio. However I resist from doing so, for the main reason that the impact of demand shocks on Surplus ratio in not straightforward as any changes in demand need to be further decomposed into durables, non-durables or services to get their impact on the Surplus ratio. Besides keeping the number of identifying restrictions small has some philosophical backing based on the principle of Occam's razor. It's the notion of 'nominalism or reductionism' (attributed to William of Occam) that in explaining something no more than necessary assumptions should be made. The identification strategy remains agnostic to the response of the 5th variable in VAR or the variable of interest. No restrictions are imposed on this variable from shocks to the remaining 4 variables in the VAR. In the benchmark model the 5th variable, or the variable of interest, is Investments. The response of the variable of interest stays agnostic in terms of Uhlig (2005) representation. Table 3 describes the identification restrictions for various variables in benchmark 5 variable VAR.

4.2.2 Identification strategy 2

The Identification strategy 2 differs from Identification strategy 1 in the following manner. The negative sign restrictions on the surplus ratio (the fourth variable in the VAR) on impact of FTS and Policy shock are removed. They are replaced by zero restrictions for both FTS shock and Monetary policy shock. So the Surplus ratio which is a ratio of the difference between total consumption and non-durable and services consumption (habits) to total consumption, does not react contemporaneously to Flight to Safety shock and Monetary policy shocks. This is done to acknowledge an alternative empirical literature which argues for a lack of contemporaneous effect of monetary policy shocks on the macroeconomic variables such as investment, output and consumption, as their data is only available with a lag. On including sign restrictions given in Identification strategy

2 (see Table 3 on page 41) the $\boldsymbol{B}_{(0)}$ and $\boldsymbol{B}_{(1)}$ matrix are modified to

$$\boldsymbol{B}_{(0)} = \begin{bmatrix} + & 0 & 0 & . & . \\ . & + & . & . & . \\ - & + & + & . & . \\ + & 0 & 0 & . & . \\ . & . & . & . & . \end{bmatrix} \quad \text{and} \quad \boldsymbol{B}_{(1)} = \begin{bmatrix} + & . & . & . & . \\ . & + & . & . & . \\ - & + & + & . & . \\ + & . & . & . & . \\ . & . & . & . & . \end{bmatrix} \tag{20}$$

4.2.3 Identification strategy 3

Identification strategy 3 has one less restriction from the previous two Identification strategies 1 & 2. In this strategy the positive impact restriction of Flight to Safety shocks on Real rates, the third variable of the VAR, is removed. So Real rates is only positively restricted to Monetary policy shocks and is left unrestricted for FTS shocks. In both Identification strategies 1 & 2, the response of Real rates had same restriction (to be positive on impact) to both FTS and Monetary policy shocks. That assumption was open to the possibility that some latent shock, which could meet the imposed restrictions of both FTS and Monetary policy shock to real rates, could be responsible for the results of the model. Identification strategy 3, breaks that link by restricting the impulse responses to Real rates from Policy and FTS shocks differently and therefore avoids the possibility of responses being driven form any common external shock. By analysing the differences between the impulse response from two different Identification strategies (1 and 3, or 2 and 3), we can get further convincing evidence of whether the shocks that this empirical exercise identifies are in fact FTS shocks.

On including sign restrictions given in Identification strategy 3 (see Table 3 on page 41) the $\boldsymbol{B}_{(0)}$ and $\boldsymbol{B}_{(1)}$ matrix are modified to

$$\boldsymbol{B}_{(0)} = \begin{bmatrix} + & 0 & 0 & . & . \\ . & + & . & . & . \\ - & . & + & . & . \\ + & 0 & 0 & . & . \\ . & . & . & . & . \end{bmatrix} \quad \text{and} \quad \boldsymbol{B}_{(1)} = \begin{bmatrix} + & . & . & . & . \\ . & + & . & . & . \\ - & . & + & . & . \\ + & . & . & . & . \\ . & . & . & . & . \end{bmatrix} \tag{21}$$

A reason for choosing different identification strategies 1, 2 and 3 in this study, is the inherent assumptions in those strategies about the key drivers and propagation channel behind the model. By assuming a direct and contemporaneous link between the shock variable and macroeconomic variables, we are assuming that forward looking rational households can anticipate the shocks and respond immediately, on the other hand by excluding such contemporaneous relationship we are testing if the shock variable is a primary driver of any change in the macroeconomic series.

Recall that the sign restrictions in 5 variable VAR are implemented for a maximum horizon of one period after the shock, i.e. the restrictions are valid for the shock period and one period after. Whereas, zero restrictions are imposed only on the impact period. The maximum lag length considered on the basis of information criteria is 4 quarters. The results of all models are tested for robustness have been tested over various horizons and other lags.

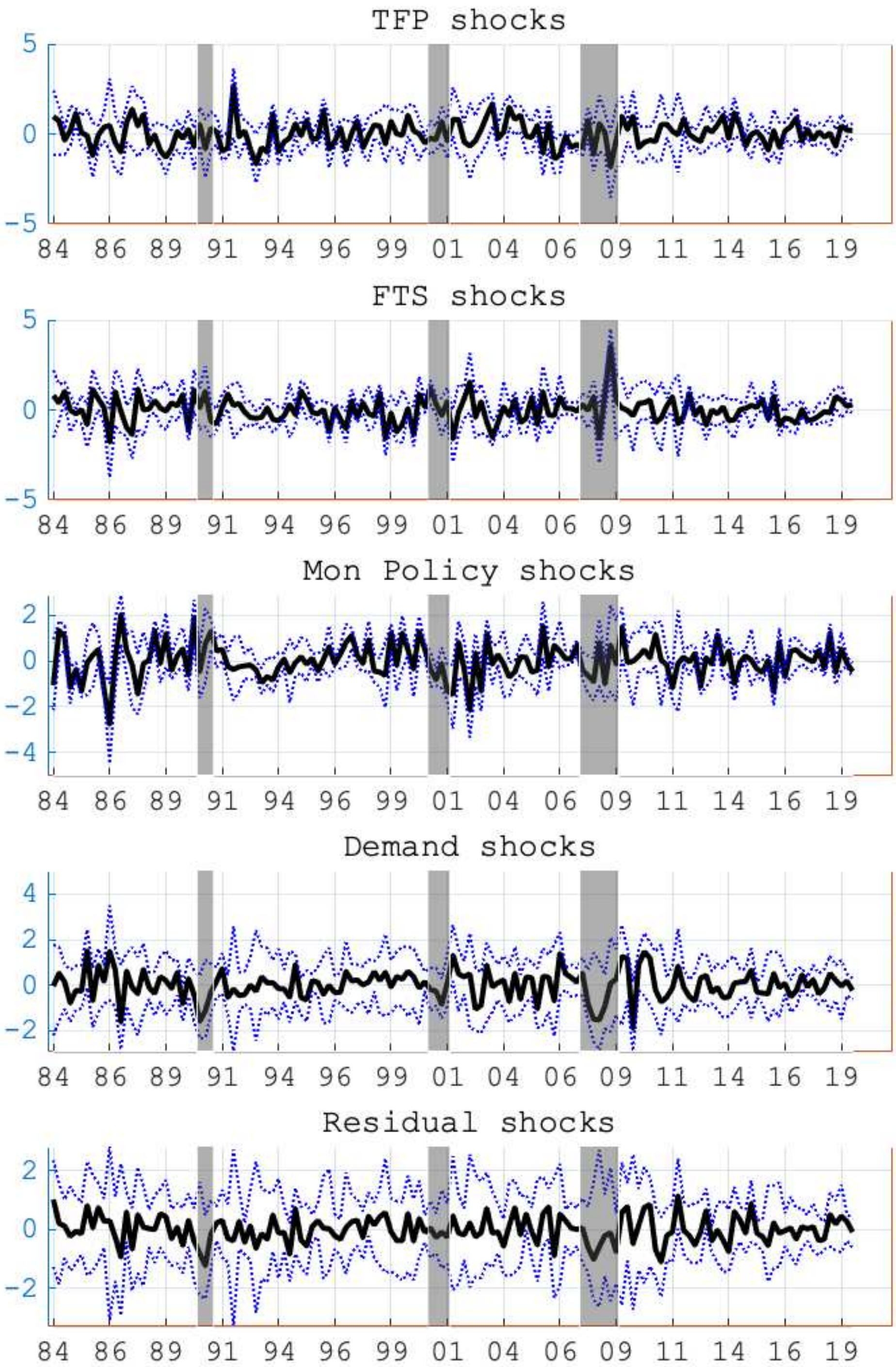
5 Structural VAR Results

This section describes the benchmark structural VAR results to show that Flight to Safety shocks inflict a long and lasting impact on the business cycle variables. The results from some investment-related variables compare well with the observed lack of investment growth in periods following the global financial crisis when economic pessimism or Flight to Safety was at higher levels. The section also shows how effective are various identification strategies in picking up innovations in Flight to Safety. It discusses the impact this identification has on beliefs about economic channels that guide investor behaviour during business cycles.

Let us first look at the identified structural shocks from benchmark VAR, which are plotted in Figure 8 on page 51, where the shaded areas represent the peak to trough dates of NBER recessions. The identified shocks correspond well with recessionary periods. The scale and size of shocks in the 1990-91 recession is smaller than in the other two recessions of 2000-01 and 2007-09. Most interestingly, only the Flight to Safety shock displays the most significant jump of its entire history during the 2007-09 recession. This brings us back to the original purpose of identifying data series and events related to the unprecedented global financial crisis more than they do so with any other post-war recession. The initial assessment portrays FTS shock as a likely candidate.

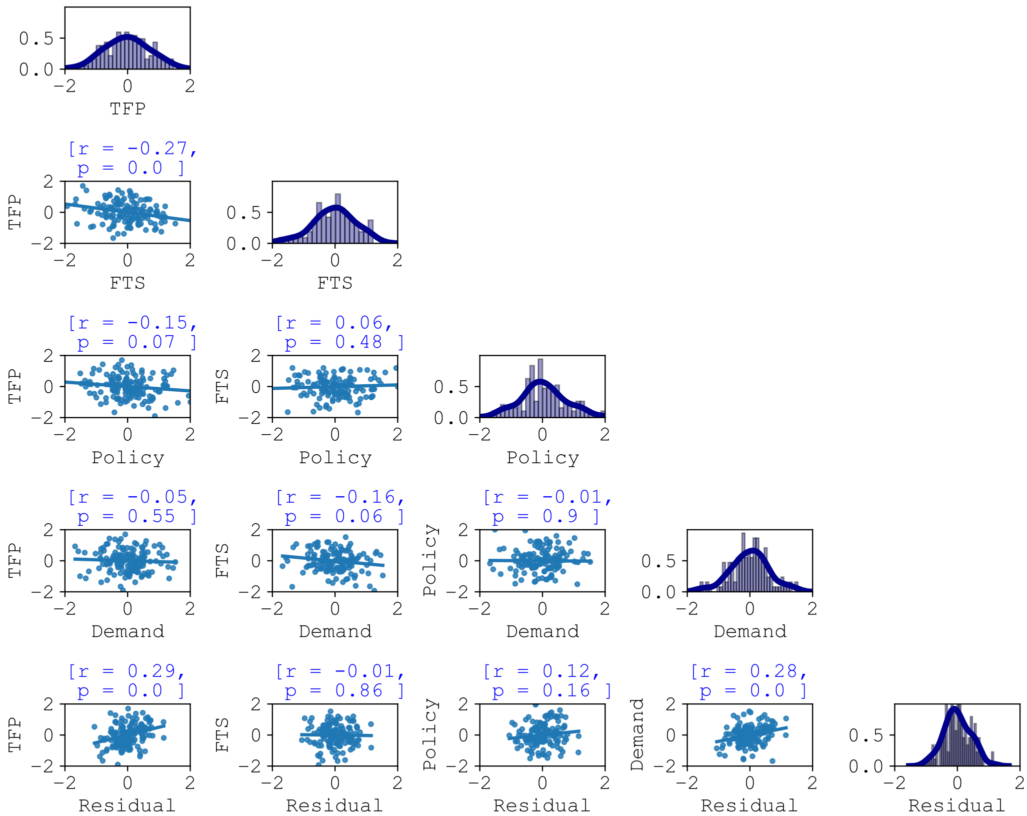
We can further assess the usefulness of the vector autoregressions in the benchmark configuration of the model by looking at identified structural shocks that are quite orthogonal (see Figure 9 on page 52) and uncorrelated. Figure 9 shows the probability distribution of these shocks, the regression line of one shock on another, and the correlation coefficients between the identified shocks. The regression line and scatter plots display a lack of meaningful relationships between the shocks. Correlation coefficients for most of them are not significant. There is some linkage in identified TFP and FTS shocks as their correlation coefficient has a small negative slope, which shows that positive FTS shocks appear to be leading to adverse TFP shocks. We further explore this feature in the following section through the results of impulse responses to FTS shocks.

Figure 8: Identified structural shocks



Notes: Standardised median structural shocks from 1983:Q1 to 2019:Q3 and their 68% confidence bands. Shocks are identified through the benchmark 5-variable VAR, using Sign and Zero restrictions discussed in Strategy 1. The 5 variables in that model are: TFP, Price of risk (Bond minus Equity price), Real rates, Surplus Ratio and Investments. The shaded areas represent peak to trough period of NBER recessions. Respective shocks are: TFP, FTS, Monetary Policy, Demand and Residual.

Figure 9: Orthogonality of structural shocks



Notes: Regression (line) of one structural shock on another, and Probability distribution of structural shocks identified in benchmark 5 variable VAR using Identification strategy 1. r is Pearson's correlation coefficient. p is Two-tailed p-value of the correlation coefficient. The 5 variables in the benchmark model are: TFP, Price of risk (Bond minus Equity price), Real rates, Surplus Ratio and Investments. Respective shocks are: TFP, FTS, Monetary Policy, Demand and Residual.

5.1 Economic contractions from Flight to Safety

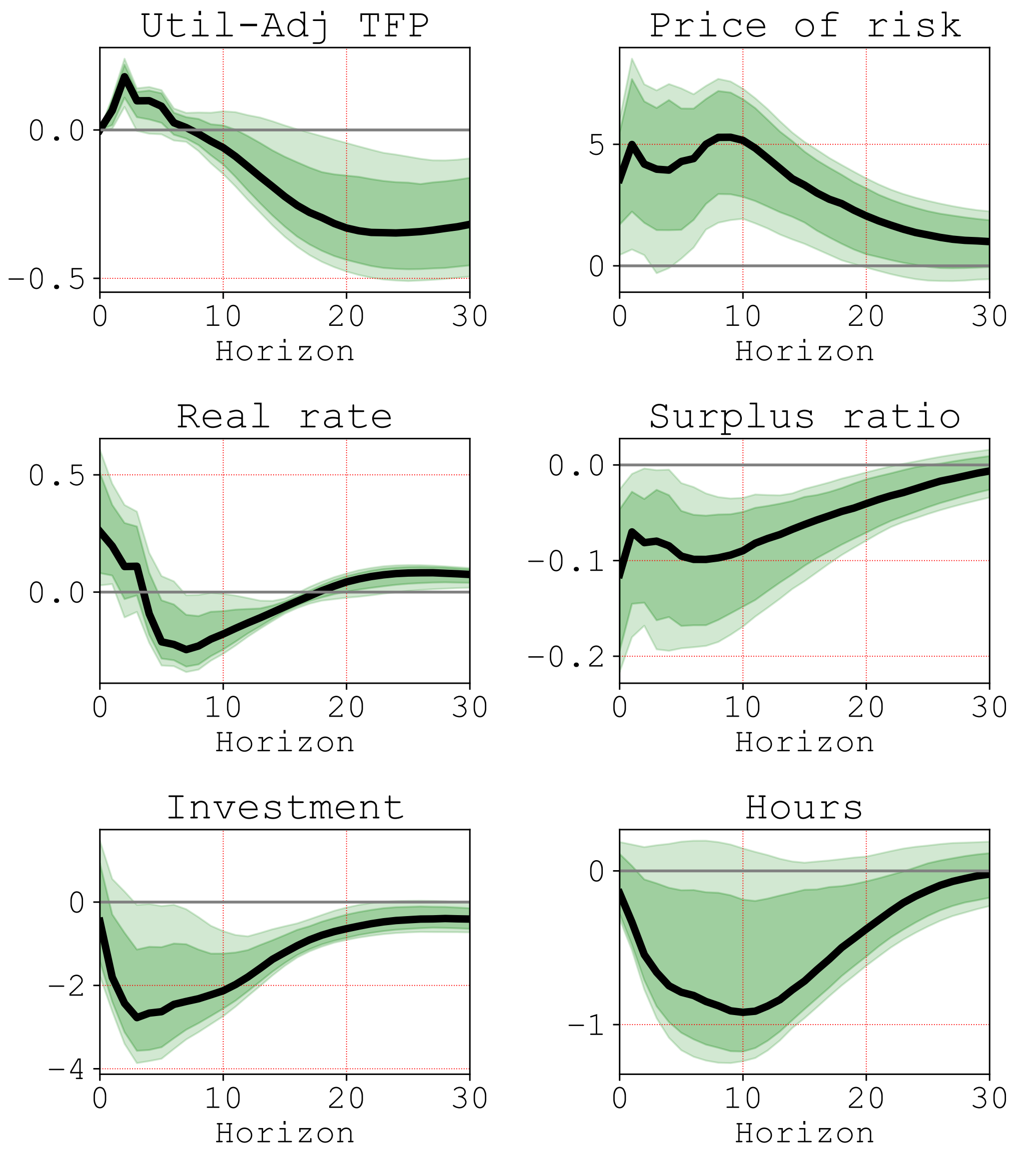
In this section, the results from identification strategy 1 (as discussed in Table 3 on page 41) for the 5 variable VAR with variables: Total factor productivity, Price of risk, Real rate, Surplus ratio, and Investments are discussed. Investments are a key variable of interest, and in later studies, it is replaced with other variables such as Output, Consumption, Hours, and CPI.

Figure 10 on page 54 plots the impulse responses from identified Flight to Safety shocks on all variables of the benchmark 5-variable VAR with Investments as the key variable that is unrestricted and considered agnostic in the identification strategy. Additionally, the figure also reports 'Hours' when replacing the variable 'Investment' in the benchmark model. Similarly, in Figure 11 on page 56 results of other variables of interests as they replace the fifth variable of the benchmark VAR are reported. The impulse response results for the first 4 variables in these alternate models are similar to those of the benchmark model where 'Investment' is the variable of interest. So, preserving space and time, they are only reported once, i.e., for the benchmark model.

The results (in Figure 10) show that the pessimism and risk aversion resulting from Flight to Safety shocks has a long term impact on the business cycle. The Bond minus Equity price (Price of risk) series jumps upon impact from FTS shocks. As described earlier, an unexpected increase in the price of a safe asset (10-year T-bond) vis-á-vis the price of a risky asset (S&P 500) symbolizes an increase in investors' preference for safety over risky investments, or Flight to Safety. So as expected from sign and zero restrictions set out in Identification strategy 1, we witness an immediate jump in this series of 4-5%. An impact of this size cannot be fully generated from an increase in the safe asset price alone. The yields on safe asset (bonds) are meager, and a 4-5% increase in prices (or a drop in yields of this magnitude) cannot be obtained without violating the Zero lower bound on bond yields. Therefore a steeper fall in S&P 500 index on impact from FTS shock is the primary driver of this sudden jump in the Price of risk series. Once the FTS shock has hit, it takes near 28 quarters for the series to return to its pre-shock levels. The identified FTS shock thus demonstrates a long term impact on the investors' preference for safer assets.

Identification strategy 1 (discussed in table Table 3 on page 41) restricts the response of Real rate to FTS shocks to be positive and Surplus ratio to be negative

Figure 10: Impulse responses of Benchmark VAR to FTS shocks



Notes: Median impulse response and 68% and 95% confidence bands of variables in benchmark VAR model to Flight to Safety (FTS) shocks of 1 s.d. which are identified with Sign and Zero restrictions strategy 1. Data: 1983:Q1 to 2019:Q3. In all charts, Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. Benchmark VAR has five variables: Total factor productivity, Price of risk (which generates the FTS shocks), Real rate, Surplus ratio is one minus ratio of consumption (non-durable goods and services) to total consumption and 'Investment'. In another iteration of the 5 variable VAR model 'Investment' is replaced with 'Hours'.

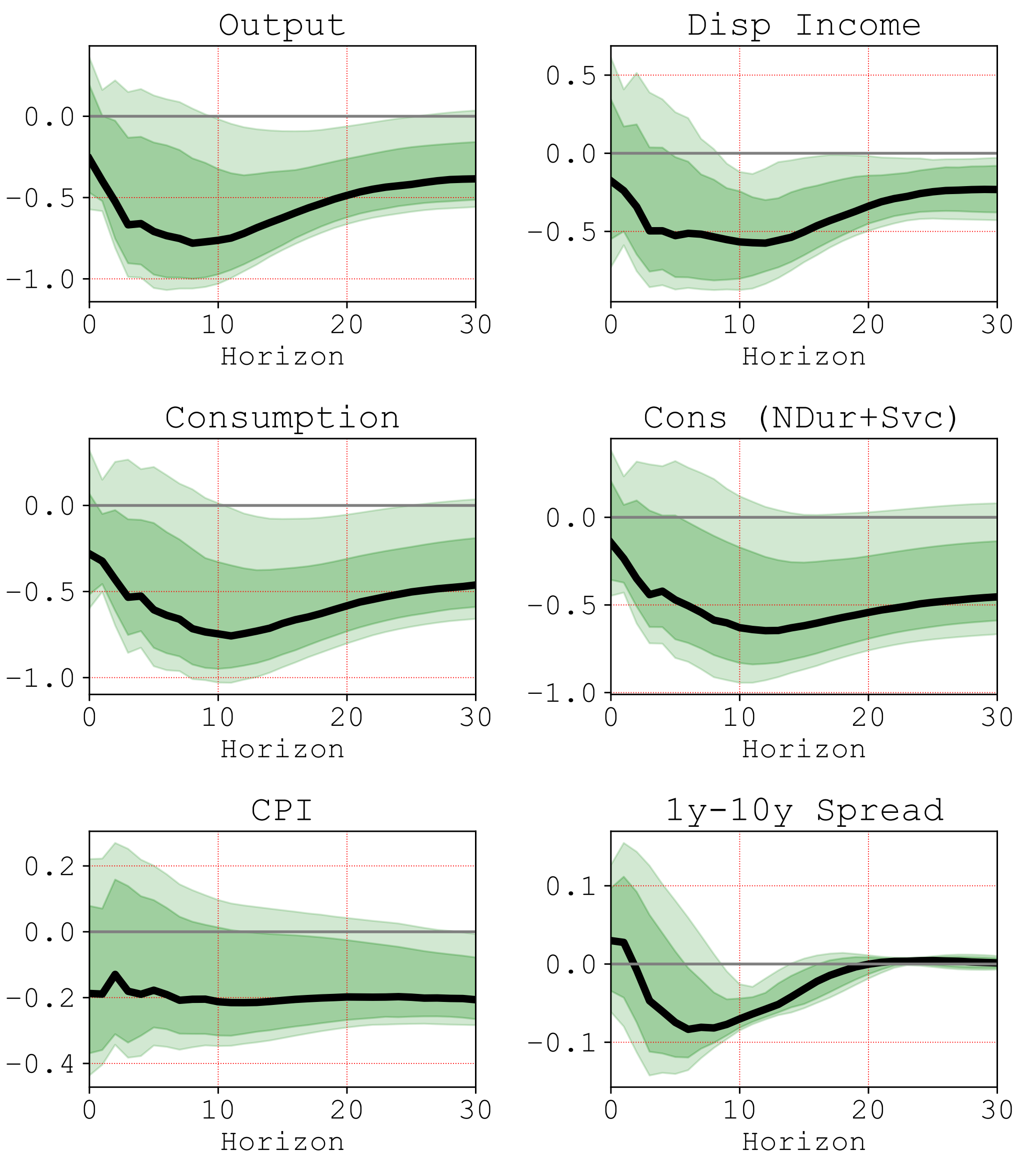
for the shock period and one period following the shock. Both these variables behave as expected. The Real rate rises, and the Surplus ratio falls on impact. The median impulse response of Real rates increases by 0.3 percent, whereas the fall in the median Surplus ratio response is about -0.1 percent. The latter is a significant fall for two reasons, the first of which is that there is not much scope for the Surplus ratio to fall. This ratio in Data in the long run averages around 12 percent, as habits (i.e., consumption of services and non-durable goods) form a significant (∼90%) portion of total consumption. Furthermore, the second reason is that the consumption-based models [Campbell and Cochrane (1999), Cochrane (2017), De Paoli and Zabczyk (2013)] which consider surplus ratio in the utility function, demonstrate that even for a small decline in this ratio there is relatively big spike in consumers' marginal utility.

The identification strategy 1 also puts a zero restriction on the response of total factor productivity so that the identified Flight to Safety shock is orthogonal to TFP. As a result, we see that the impulse response of TFP is muted on the impact of the FTS shock. However, it begins to turn negative around 8-10 periods after the shock and slides after that for another 12 quarters. For the length of business cycle frequency (8-32 quarters) after the FTS shock, there is a persistent decline in TFP.

Investment, which is the variable of interest in the benchmark 5-variable VAR, is kept unrestricted as no sign or zero restrictions are imposed on it from any shocks in the model. The impulse response in Investment is negative on the initial impact of FTS shock. Investment decisions are made many periods in advance, explaining the smaller immediate drop in Investments on the impact of the Flight to Safety shocks. However, the response reaches a median quarterly fall of around -3% in a short span of 2-3 periods after the shock. It sustains this L-shaped response and stays below -2% for about 10-12 quarters. The impulse responses also show that Investments are very slow to recover to their pre-shock levels. What is probably more significant is that after the impulse response in Investment reaches its lowest, i.e., 3-4 quarter after the impact of FTS shock, only then the Total factor productivity (TFP) begins to decline.

To better understand the mechanism through which FTS impacts the business cycle, 'Investment' in the benchmark configuration is replaced with other macroeconomic variables. They are 'Hours' whose impulse responses to FTS shocks are presented in Figure 10 on page 54 itself and six other variables. Impulse responses to FTS shock for these six variables are presented in Figure 11 on page 56. These

Figure 11: Impulse responses of Macro variables to FTS shocks



Notes: Median impulse response (in %) and 68% and 95% confidence bands of Macro variables of interest to Flight to Safety (FTS) shocks of 1 s.d. in benchmark VAR model identified with Sign and Zero restrictions strategy 1. Data: 1983:Q1 to 2019:Q3. In all charts, Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. Only the responses of variable of interest in the VAR model are reported. 'Disp Income' stands for Disposable Income. '1y-10y spread' is the difference between yields of 1 year and 10 year US Treasury bonds. 'Cons (NDur + Svc)' is Consumption of Non-durable goods and Services.

additional variables include four business cycle variables: 'Output', 'Disposable income', 'Consumption (Non-Durables and Services)' and total 'Consumption', a pricing variable 'CPI' and a liquidity variable '1y-10y spread' which is the difference in the yields of 1-year and 10-year US treasury bonds.

The impulse responses to these variables represent a negative hump-shaped response. 'Hours' exhibits a negative response that is slow to begin and decreases gradually, which resembles a reverse hump shape. However, except for hours neither of the other business cycle variables fully recover to their pre-shock levels. The median response in hours is small and reaches a minimum of approximately -0.9% around 10 periods after the shock. In contrast, the TFP for the first 8-10 quarters has been non-negative, which means the decline in hours is not driven by technical regress. Similarly, the responses in other variables of interest - Output, Disposable Income, Consumption (Non-Durables and Services), and Consumption - cannot be linked to a fall in TFP. It can be argued that their fall is more synchronous with Flight to Safety. Since after the Flight to Safety (FTS) shock has hit, the impulse response in these variables keeps on reducing for 10 periods, whereas for the same period after the shock, the TFP is non-negative.

It also seems that the impact of Flight to Safety shocks on macro variables must be playing out through a long-term decline in Investments. The impulse response in Investments has a faster and a more significant decline, almost 3-4 times of the decline witnessed in Hours, Consumption, Output, Consumption (of Non-durables and Services) and Disposable income. The negative impact on these macro variables of interest continues for 8-10 quarters before reaching its nadir and recovering after that. 8-10 quarters is also the time around when the steep fall in Investments begins to ameliorate. Therefore we can safely say that TFP shocks do not bring the economic gloom that is shown in 'Investments' and other variables of interest. Instead, it is driven by the pessimism in the economy brought out from a structural FTS shock.

This highlights the investment-oriented effects of FTS shocks, and provides evidence to one of the hypotheses set out at the inception of this study. Flight to Safety, which is a sudden change in preference for safer investments by investors through resource re-allocation, leads to an eventual decline in overall TFP. As when only safer (or less productive) economic investments are undertaken, the entire economy's production and productivity suffers.

One could also argue that the economic contraction is unrelated to TFP declines and is caused by FTS shocks. This contradicts other studies in the literature that follow the (Barro and King, 1984) conjecture, which has argued that investment re-allocation is not a major driving force of the business cycles. Several empirical studies on the news [Beaudry, Nam, and Wang (2011) Nam and Wang (2019)] and expectations shocks identify that those shocks only lead a TFP shock by 1-2 quarters. Therefore, the TFP shock appears to cause changes to macro variables and business cycles in those studies. The long lead time between FTS shock and TFP shock that we get in impulse responses of Identification strategy 1 breaks that link and leads us in seeking an alternate driving mechanism.

Habits or Consumption (Non-durables and Services) are also slow to react initially upon the impact of the FTS shock, but they end up mimicking the decline in Consumption and after 30 periods end up about -0.5% lower that their pre-shock levels. This is significant for two reasons. Firstly, it shows that the precautionary motives exhibited during FTS generate a correction in even the most hard-wired of consumption behaviour (habits). Secondly, for a consumer looking for her utility maximization, a stabilization of the surplus ratio (i.e., one minus the ratio of habits to total consumption) matters more than stabilization of total Consumption or Habits. This is further explored in later chapters.

The median response of term spread, in Figure 11, which is measured as the difference between the short-dated 1-year US Treasury bond and the long-dated 10-year US Treasury Bond yield, picks up slightly on the impact of the FTS shock. However, the move is not significant, especially when compared to the rise in the Price of risk. It demonstrates that the preference for safety that is a hallmark of an FTS shock does not significantly translate into a preference for liquidity, i.e. preference for the short term over long term safe bonds. This is not surprising since most long-term investors such as pension funds would match the duration of the risky assets that they are shedding from their portfolio with the duration of the safe investments they are undertaking in response to the FTS shock.

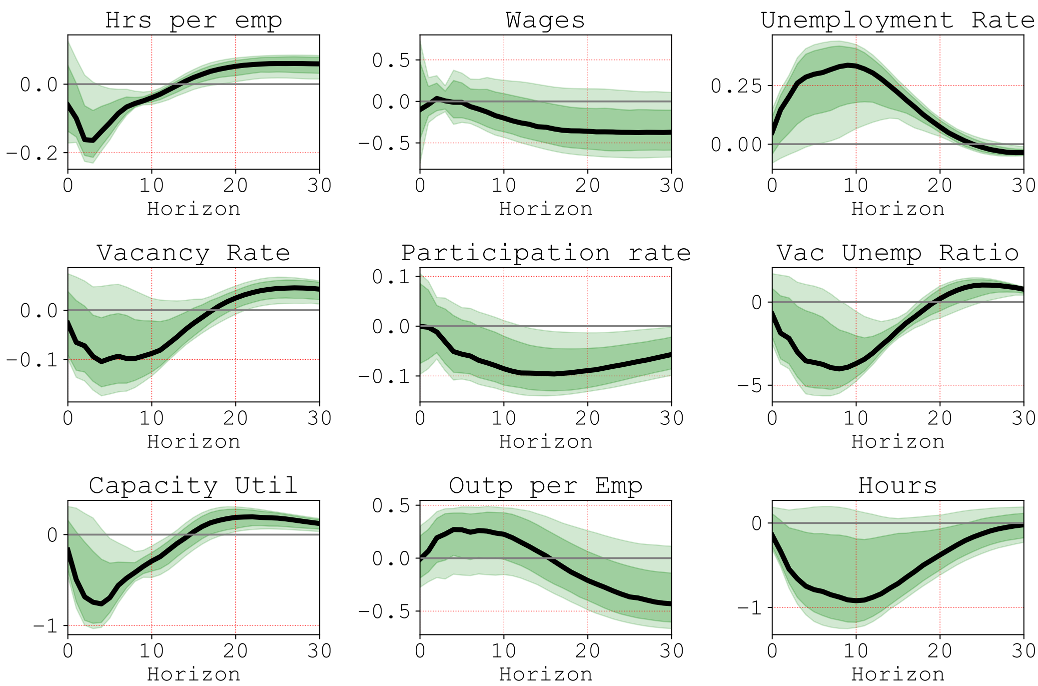
The impact of FTS shock on consumer prices (CPI) supports our conviction of imposing a positive restriction (in Strategy 1) on Real rates from the impact of FTS shock. The rationale for such restriction was that a Flight to Safety shock is dis-inflationary, and the evidence in the impulse response of CPI confirms it. The median CPI falls around 0.2% per quarter, or we can say there is a deflation of 0.2% quarterly deflation on the impact of FTS shock. The median CPI does not recover for the tested horizon of 30 periods, which for the quarterly inflation rate means that a few quarters after the Flight to Safety shock, the inflation rate consolidates around zero percent. This shows that FTS shock is deflationary on impact and non-inflationary in the long run, a sign of economic pessimism. Thus looking at the impulse responses of various macro variables, we can make an assessment that a Flight to Safety shock leads to an overall economic gloom in the economy.

The results highlight the fact that either one of the two possible channels of *speculation* or *expectations* through which FTS can impact the economy is at play. The *speculation channel* relies on FTS resulting from over-correction by speculators from a realization of negative news or information shock about the economy. If that were true, then the economic adjustment to FTS would have been swift. Nevertheless, given the slow but significant response of key Investment and activity-related variables to FTS shock and the long lead time of 8-10 quarters in the decline of total factor productivity after the FTS shock indicate that *speculation* may not be the primary mechanism driving this effect. The *expectations channel* relies on the notion that Flight to Safety emerges from expectations being formed about the deteriorating future state of the economy. It posits that FTS shocks are based on rational expectations and present a warning signal of an eventual decline in economic activity. If this were true, then FTS is an even earlier warning signal than news and sentiment shocks, where the lead time is usually 3-4 quarters. This seems plausible, as FTS represents an increase in risk-aversion, so providing a warning of impending deterioration in the economy motivates risk-averse rational agents to reallocate investment capital from risky to less risky (and also less productive) sectors. This re-allocation of risk over time feeds into a decline in economic activity and a decline in total factor productivity. This paper's empirical approach is not sufficient to distinguish between the two, but some clarity can emerge from looking at various impulse responses from different identification schemes. Through evidence posted by various macroeconomic variables, there is some inclination towards favouring the latter *expectations driven* explanation that FTS shock predates an economic downturn. We can further strengthen this conviction from the results of Investment and Labour related business cycle variables.

5.2 Cyclicality of Labour and Investment sector

To provide further evidence that identified FTS shocks consistently explain the properties of US business cycles, this section compares the impulses responses in

Figure 12: Impulse responses of Labour variables to FTS shocks



Notes: Median impulse response and 68% and 95% confidence bands of Labour related variables of interest to Flight to Safety (FTS) shocks of 1 s.d. in benchmark VAR model identified with Sign and Zero restrictions strategy 1. Data: 1983:Q1 to 2019:Q3. In all charts, Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. Only the responses of variable of interest in the VAR model are reported. 'Hrs per Emp' is Hours worked per employee. 'Vac Unemp' is ratio of Vacancy rate to Unemployment rate.

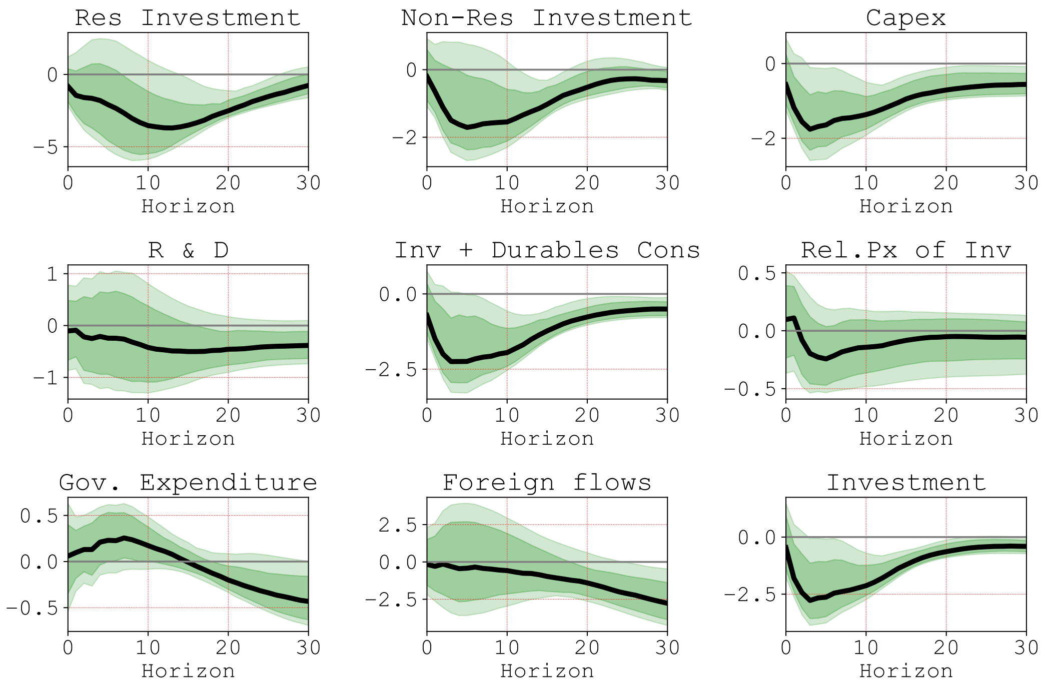
Identification strategy 1 (see Table 3), of a 5-variable VAR model where either a labour market variable (Figure 12) or an investment sector variable (Figure 13) is the variable of interest. Recall that in this identification the impact of TFP shock is restricted to be positive on the utility-adjusted TFP and Surplus ratio, and is restricted to negative on Real rates. The impact response of FTS shock is positive on the Price of risk (Bond-Equity price), positive on Real rates, and negative on Surplus ratio. The Monetary policy shock impact is restricted to positive on Real rate and negative on the Surplus ratio. Both FTS and Monetary policy shock are orthogonal to TFP shock.

The identified FTS shocks substantially impact unemployment rate and labour force participation rate (Figure 12 on page 60). Hours per worker decline slightly on the FTS shock impact and recover fast; also, they are not the major driver of total hours. These responses agree with Shimer (2005) empirical result that the major driver of the decline in total hours is not hours per worker but the unemployment rate. The intensive margin, given by hours per worker, is only partially responsible for fluctuations in aggregate hours and other labor market constituents.

The impulse responses to the Vacancy rate and the Unemployment rate are opposite to each other, signifying the negative correlation between the two at business cycle frequencies. Search based models of unemployment and business cycles (of which Mortensen and Pissarides (1994) is a key example) cannot generate the high negative correlation between the unemployment and vacancy rate. Due to the Nash bargaining mechanisms, the real wage determined in these models is too flexible (Shimer, 2005).

The results from Flight to Safety shocks generate a vacancy to unemployment ratio that is procyclical and a real wage rate that is highly sticky and in line with the *Beveridge curve* that portrays a downward sloping relation between the Vacancy rate and the Unemployment rate in the US data. The Labour force participation rate in our results is also procyclical. The impulse responses (in Figure 12) for labour productivity, which is the ratio of output to hours, exhibits an increase on the impact of FTS shocks. Whereas Hours, Output, Consumption reduce during the first 10 periods after the shock. This incongruity of response of labour-related business cycle variables with the response of TFP and labour productivity shows that the key driver behind this economic gloom is not the decline in TFP but rather an increase in economic pessimism breeding the Flight to Safety. This finding contradicts the economic models that ignore the role of

Figure 13: Impulse responses of Investment variables to FTS shocks



Notes: Median impulse response and 68% and 95% confidence bands of Investment related variables of interest to Flight to Safety (FTS) shocks of 1 s.d. in benchmark VAR model identified with Sign and Zero restrictions strategy 1. Data: 1983:Q1 to 2019:Q3. In all charts, Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. Only the responses of variable of interest in the VAR model are reported. 'Res' is Residential, 'Non-Res' is Non-Residential, 'Inv + Durables Cons' is sum of Investments and Durables Consumption, 'Rel.Px of Inv' is the Relative price of Investment in terms of Consumption, 'Gov.' stands for Government.

expectations and cyclical risk-aversion in business cycles.

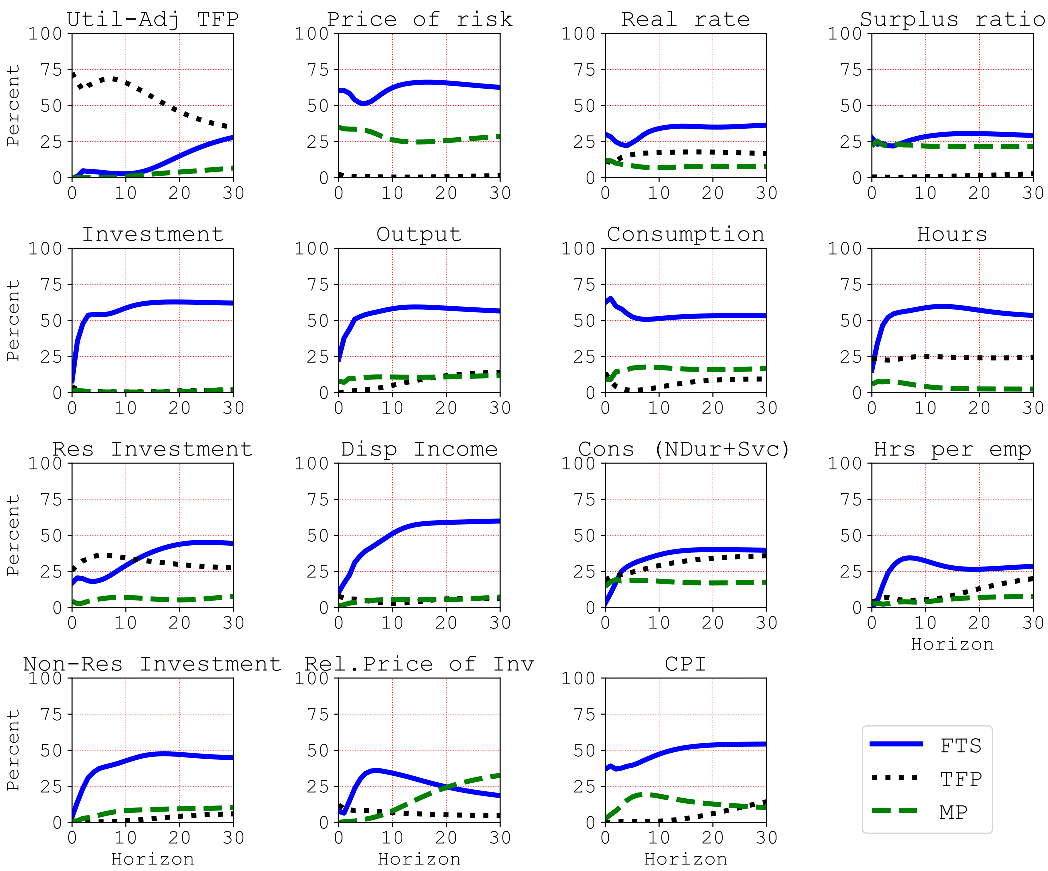
Further investigation into the constituent variables of investments, i.e., residential and non-residential investment (See Figure 13) shows that the residential investments react slowly to the FTS shock. However, after around 10 periods, it reaches a median reduction of -4% per quarter. Most housing-related investments are planned for many periods in advance. Once the residential investment projects are approved, they are slow to roll back, and once these plans are stalled or abandoned, they are even more challenging to get re-approved. On the other hand, non-residential investments that are more agile in comparison react early on the shock's impact. They consolidate after about 5 quarters at a median response of -2% per quarter and recover faster than residential investments. Capital expenditure is held back by -2% and is faster to react than residential and non-residential investments. The FTS shocks have a lesser impact on R&D expense which is a more stable form of investments. Similarly the consumption of the Durable goods of households, a part of Investment plus Durable series, is steadier than total investments. It declines by a little over -2% upon the impact of an FTS shock. The impact of FTS shocks on both Government expenditure, and Foreign flows are felt only in the long run. More importantly, FTS shock on impact lowers the relative price of investment good (in terms of consumption).

The variable 'Relative price of investment' in business cycle literature has been used as a series to develop investment-specific technology shocks and the marginal efficiency of investment shocks. The Flight to Safety shocks identified in this study do not run against the investment shocks literature-based evidence. A positive shock to investments lowers the relative price of investment in terms of the consumption good in models of Justiniano, Primiceri, and Tambalotti (2010) and (2011), and J. Greenwood, Hercowitz, and Krusell (2000) among others. The procyclical relative price of investments, which is a hallmark of investment-specific technology shocks-based explanations of business cycles, is also visible in this chapter's impulse responses. The ratio of investment price to price of consumer good falls on impact of the FTS shock, i.e. consumption becomes relatively expensive.

An immediate application of the findings is to get decomposition of forecast error-variance (See Table 6 to 10 in appendix pages 118 - 122) and to determine what proportion (Figure 14 on page 64) of the k-step ahead forecast variation, esp. at business cycle frequency (8-32 quarters) is explained by identified innovations to FTS.

The FTS shock explain a major share of Forecast error variance at business cycle frequency for each of the key business cycle variables: Output (58%), Consumption (50%), Investment (60%), Residential Investment (40%), Income (55%), Hours (55%), TFP (20%), Surplus ratio (30%), Real rate (35%). The FEV contribution for FTS shocks to key macro variable peaks before an increase in contribution from TFP shocks. Suggesting that FTS shocks rather than TFP shocks drive the highlighted business cycle features.

Figure 14: FEVD explained by TFP, FTS and MP shocks



Notes: The k-step ahead Forecast error variance decomposition (FEVD %) explained by FTS (Solid), TFP (Dots) and Monetary Policy (Dash) shocks, in the 5-variable VAR, which is identified using Sign and Zero restrictions discussed in Strategy 1. The 5 variables in the benchmark model are: TFP, Price of risk (Bond minus Equity price), Real rates, Surplus Ratio and Investment. In other iterations of the model, 'Investment' is replaced with other variables of interest. The result of benchmark VAR and other variables of interest are reported.

Table 4: Identification strategy for Flight to Risk shocks

variables / *shocks*	TFP	Value of Risk	Real rate	Surplus ratio	Variable of interest
FTR Strategy 1					
Productivity	+	.	−	+	.
Flight to Risk	0	+	−	+	.
Monetary policy	0	.	+	−	.
Demand	.	.	.	.	.
Residual	.	.	.	.	.

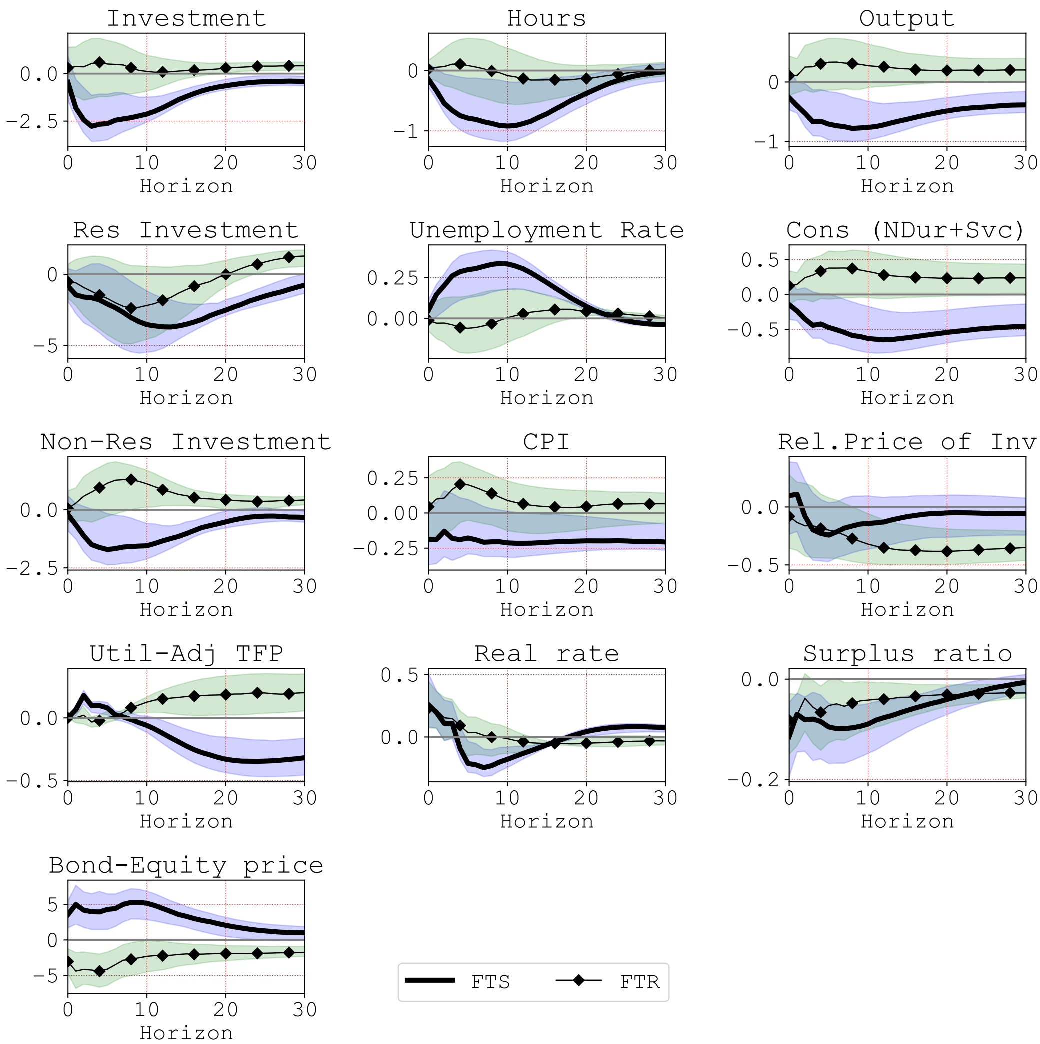
Notes: The SVAR for identifying Flight to Risk shocks has 5 variables: TFP, Value of risk (which is Equity price minus Bond price), Real rate, Surplus ratio (which is One minus the ratio of Consumption of services and Non-durable to Total consumption), and a business cycle variable of interest for e.g. Investments , Output, Consumption, Hours, CPI etc. On impact of the respective shock, + means the variable is restricted to be positive and − means that the variable is restricted to be negative for the impact horizon. The impact horizon is shock period plus one more period. Symbol 0 signifies a zero restriction when the response variable is restricted to not respond to the shock contemporaneously, and Dots . signify that the impact response of that variable is left unrestricted.

5.3 Asymmetry in FTS and FTR

One of the peculiar and significant features of Flight to Safety (FTS) or a sudden increase in preference for safer investments is that the market volatility and uncertainty experienced in such episodes are not reciprocated during its complementary market phenomenon of Flight to Risk (FTR). FTR is when investors prefer risky investments to safer bets. Such differential behaviour is based on the human psyche and behavioural biases that are out of this study's scope. However, for the purpose of our analysis, it is interesting to consider whether the impact of FTS is reversed for shocks of opposite magnitude. An FTR shock series is developed by choosing a complementary identification to the one imposed in the benchmark study. Impulse response results from this series help uncover FTR shocks' impact and keep the analysis relevant and comparable to the benchmark FTS model results.

The FTR shocks are identified by changing the sign of the Price of risk series, i.e. by calculating it as the difference between the Price of S&P 500 and the

Figure 15: Asymmetry between Flight to Safety and Flight to Risk



Notes: The figure shows impulse responses to Flight to Safety (solid) and Flight to Risk (diamonds) shocks and their 68% confidence bands (shaded). FTS shocks are identified with restriction strategy 1 in the benchmark VAR model. The FTR shocks are identified by imposing restriction strategy discussed in the Results section Table 4. Data: 1983:Q1 to 2019:Q3.

10-year Treasury bond. This could be called a Value of Risk series or negative Price of risk series. Therefore an increase in the Value of Risk or Equity minus Bond price series occurs when Equities get more expensive compared to bonds, and a positive shock to this series is studied as Flight to Risk. The identification strategy imposed in identifying FTR shocks is also adjusted to account for the complementary changes to benchmark strategy 1. A positive shock in the Value of Risk series for the impact horizon is restricted to a fall in Real rates and an increase in the Surplus ratio. Both these sign restrictions are opposite in signs to the sign restrictions imposed on these variables in the benchmark strategy 1 for identifying FTS shocks. Similar to FTS shocks the FTR shocks are also restricted to be orthogonal to TFP and monetary policy shocks. Table 4 on page 65 presents the identification restrictions imposed in identifying FTR shocks. The impulse responses to FTR shocks, as shown in Figure 15 on page 66, highlight the asymmetry in the response of Flight to Safety and Flight to Risk shocks. These impulse responses to FTR shocks are smaller in magnitude and short-lived compared to the impulse responses to FTS shocks. The increase in Equity minus Bond price (or a decrease in Bond minus Equity price) from an FTR shock leads to very slow adjustments in investments, hours, output, non-residential investments, inflation, and TFP and real rates when compared with their response to FTS shocks. The lack of negative response in Real rates is because monetary policy response is exogenous to the model. An increase in inflation after Flight to Risk does not warrant policy cuts from the inflation-targeting central bank. Real rates become negative when inflation stabilizes. The residential investment shows a lack of response, which is not that puzzling when considering that residential purchases are long-term decisions. These can be put away easily when faced with a Flight to Safety phenomenon, but they are not immediately put on board after a Flight to Risk. Housing is a long-term investment, and in the case of Flight to Risk shocks, the immediate response should be felt in more volatile (risky) but liquid options. The residential investment increases after 5 years of risk-taking. There is also a counter-intuitive fall in surplus ratio after an FTR shock. However, it can be explained by the slow response of output and consumption in comparison to the more significant increase in consumption (of Non-Durables and Services) habits. The increase in habits is also responsible for the relative price of investment goods in terms of consumption good getting into the negative territory. The surplus ratio slowly returns to its pre-shock levels. There is also feedback from FTR shocks to TFP, which reacts positively 5-8 quarters after the shock. Interestingly the response is delayed as it was in response to FTS shocks, highlighting the expectations channel through which the capital flight can impact productivity in an economy.

6 Sensitivity and Robustness analysis

The benchmark results are identified with Strategy 1 and using 1983:Q1 to 2019:Q3 period US data. This section analyses the sensitivity of those results to alternative identification strategies *viz.* Strategy 2 and Strategy 3 (given in Table 3). And to alternative data periods *viz.* pre-Great Moderation data (1954:Q3 to 1978:Q4) and pre-financial crisis or Great Moderation period of 1983:Q1 to 2007:Q2. This section also compares FTS results with estimation output from DSGE models and explores the relationship of FTS shocks with other News and Uncertainty shocks.

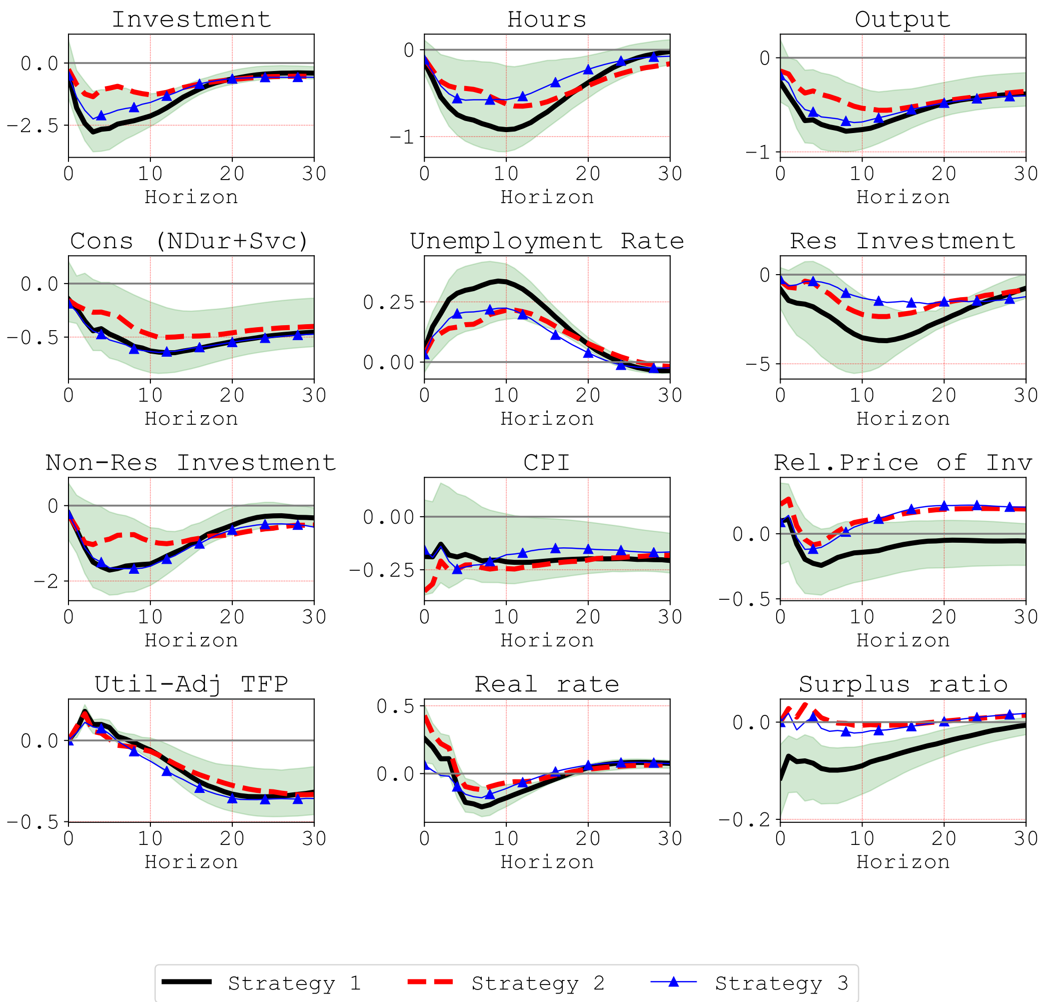
6.1 Alternative identification strategies

In Identification strategy 2 (refer Table 3 on page 41), the negative restriction on the impact of FTS shock to surplus ratio, which was included in Identification strategy 1, is removed. In place of that, a zero restriction is imposed on the Surplus ratio on impact from the FTS shock. The impact of FTS shock on Real rates is still kept, as it was in Identification strategy 1, at positive for the impact horizon, i.e., the shock period and the next period. In addition, the response of the Surplus ratio in the identification strategy 2 has a Zero restriction on impact from Monetary policy shock as well.

Changes in identification strategy 2 can be summarised in the following way. An increase in FTS is restricted to a positive impact on Price of risk and Real rates, Monetary policy shock is restricted to have a positive impact on Real rates, and both FTS and Monetary shock are orthogonal to the Surplus ratio. Whereas, in this strategy, the impact restrictions for TFP shocks are unchanged from Identification strategy 1 and are orthogonal to both FTS and Monetary policy shock. The responses of the variable of interest, which is Investment or any other macro variable, are kept agnostic.

The impulse responses to FTS shocks under Identification strategy 2, which are plotted as dashes in Figure 16 on page 69, are not significantly different from the responses to Identification strategy 1, which are represented by a solid line with its 68% confidence band is shaded in the same fig. 16. The decline in Investments is severe and keeps around -2% for around 10 quarters. The impulse responses in

Figure 16: Sensitivity of impulse responses to identification strategies



Notes: Sensitivity of impulse responses to FTS shocks under identification with Benchmark Strategy 1 (Solid) with responses from Strategy 2 (Dash) and Strategy 3 (Triangles). Data: 1983:Q1 to 2019:Q3. 68% confidence band of Benchmark strategy is shaded in light green. Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. 'Cons (NDur+Svc)' is Consumption of Non-durable goods and Services. 'Res' is residential, 'Non-Res' is non-residential, and 'Rel.Price of Inv' is Relative price of investment good in terms of consumption good.

key business cycle variables of interest such as hours, output, and consumption are immediate (See Figure 16) and are shaped in an inverse hump. The reduction in Consumption (non-durables and services) and the Surplus ratio is delayed by 2 periods, and the response is now less severe than it was in identification strategy 1. The response of the Surplus ratio stabilizes to pre-shock level as Habits fall in line with Consumption. The median response reaches a minimum of only -0.04%, which is due to the differences in identifying restrictions between Strategy 1 and Strategy 2. More importantly, the response of TFP is muted for around 10 periods and is nearly as severe as it was during the identification strategy 1. This exercise in identification strategy 2 shows that the Surplus ratio restriction was not driving the future decay in TFP. Instead, it further supports the argument that the FTS shocks predate, by a significant period, an imminent fall in TFP.

Identification strategy 3 is different from identification strategy 2 and strategy 1 concerning restrictions based on FTS shocks. The restriction imposed (in strategy 1 and 2) on the real rate response to be less than zero on the FTS shock impact is removed, and this variable is made unrestricted to the FTS shock. But the zero restrictions to TFP and Surplus ratio variables are kept, as they were in Identification strategy 2. Therefore Price of risk (Bond minus Equity prices) is the only variable that is restricted to increase on the impact of a positive FTS shock. The impact restrictions for TFP shocks are unchanged and are kept the same as they were in identification strategy 1 and identification strategy 2. The monetary shock has restrictions for only the Real rate to be positive for the impact period (shock period and the next period) horizon and has zero restrictions on the impact of the TFP series and the Surplus ratio. The impact response from the variable of interest is unrestricted and kept agnostic.

Thus Identification strategy 3 is a way to distinguish between the responses of FTS and Monetary Shocks. By removing the restriction on Real rate upon the impact of FTS shocks, we would like to ascertain if the shocks that we have identified are FTS shocks and are not driven by some exogenous shocks that impact both FTS and Monetary policy shocks similarly.

The results from identification strategy 3 are represented by triangles in Figure 16 on page 69. They differ from our findings from the results of the first 2 identification strategies. Once we take out the impact restriction on Real rate to be positive for an FTS shock, the real rates' median response is only slightly positive +0.1% on impact, whereas the fall in CPI upon impact from the FTS shock is -0.2%. This result should not be puzzling as it shows that the jump in Real rates from FTS shock is cut short by a simultaneous response of the Monetary policy, or a cut in nominal rates. It signifies that FTS shocks are co-incidental with cuts in policy rates, which further strengthens our initial hypothesis of the FTS shock being a pre-cursor of worsening economic climate.

By removing the restriction on response of Real rates in Identification Strategy 3, we can also remove the constraints on contemporaneous changes in monetary policy in response to FTS shocks. This leaves the interest rate policy some scope to be pre-emptive. Therefore the cuts in real rates in this strategy occur earlier compared to rate cuts in strategy 1 and 2. Through this, we witness that the delay in the response of TFP to FTS shocks is also shortened. Evidently, the TFP begins to decline after 5 periods, whereas it declines 8-10 periods after FTS shocks in identification strategy 1. Hours, output, consumption, and investment all exhibit a faster decline (or a shorter slump) and reach the minimum around the same time, i.e., 5 periods after the shock, when total factor productivity growth becomes less than zero. The main result from different identification strategies reinforces the conviction of results of identification strategy 1, which is that the innovations in Price of Risk (Bond minus Equity prices) predate a general economic slump, which in around 8-10 quarters also leads to an eventual decline in TFP.

Next, we look to address the possible criticism that the chosen data period in our benchmark configuration period of 1983:Q1 to 2019:Q3 is heavily influenced by the increase in the supply of safe assets around the world since the global financial crisis and by the impact of the crisis itself. This criticism is addressed by curtailing the analysis to the pre-crisis period of 1983:Q1 to 2007:Q2, which is also the Great Moderation period. We also consider the sensitivity of the results to the pre-Great Moderation period of 1954:Q3 to 1978:Q4, intending to understand the influence of great moderation on the strength of Flight to Safety shocks.

6.2 Impact of Great moderation period

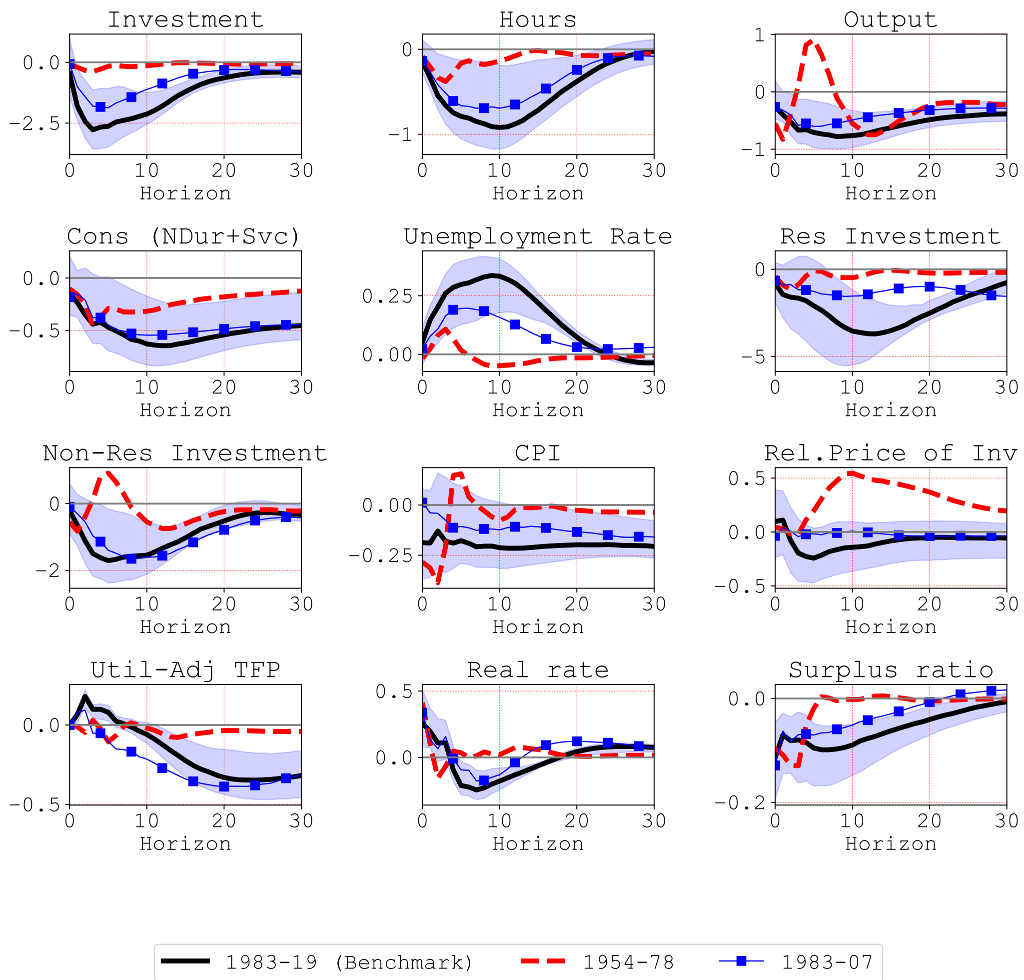
From the mid-80s to global financial crises, the Great moderation period represents a period in the macroeconomic history of developed economies when the incidence and volatility of business cycle fluctuations were significantly reduced from the decades that preceded it, 1954 to 1978. Structural developments in public policy and the Federal reserve's policy commitment and communication strategy were influential in bringing out this change in business cycle incidence and volatility during the Great Moderation period. It is argued that economic agents were better able to form expectations about future economic and policy uncertainty during great moderation than in the decades that preceded it.

The results of this empirical study show us that FTS shocks breed in pessimism about the general economic climate that predates an eventual decline in future TFP. One of the reasons this is possible is if FTS shocks signal households to expect future TFP and economic growth to be weaker. If these expectations are well-formed, then in line with the Great moderation literature, they must be significantly well-formed in the Great moderation era 1983-2007 than in the volatile era 1954-1978. Figure 17 on page 73 shows the median impulse responses to FTS shocks for business cycles variables of macroeconomic variables of interest for the pre-Great moderation period (1954-1978) in dashes, and the Great Moderation period (1985-2007) in squared line. This figure also compares these two periods with the benchmark period (1985-2019) median response given in a solid line. The shaded area depicts 68% confidence bands for the benchmark period responses.

It is clear from the results that the FTS shock has a limited impact during the pre-Great moderation period (dashes in Figure 17). This suggests that FTS shocks have been more critical in the Great moderation period. Due to the available technology, structural policy changes and low inflation in this period, it was easier to form expectations about the future TFP growth. Moreover, through improved trading opportunities and increased participation from retail investors, there has been an increase in availability and awareness about risky and safe assets in the Great moderation period as compared to the earlier period. The impact of the global financial crisis is also visible through the comparison of Great Moderation (squares) and the benchmark period (solid) results in fig. 17. The inclusion of post-Global financial crisis data accentuates the responses in unemployment and residential investments. What stands out most from the result is that during the Great Moderation, the response of investment, hours, real rates, utilization-adjusted total factor productivity is similar in scale and scope as predicted by the benchmark model. It reinstates our conviction in the results that FTS shocks generate business cycle fluctuations.

Thus from the various identification strategies, periods, and business cycle variables employed in this empirical study, we can confirm that the identified FTS shocks of the Price of risk (Bond minus Equity price) series are linked to

Figure 17: Sensitivity of impulse responses to different time periods



Notes: Sensitivity of impulse responses to FTS shocks during Benchmark period 1983:Q1 to 2019:Q3 (Solid) with responses from Pre-Great moderation period 1954:Q3 to 1978:Q4 (Dashes) and Great Moderation period 1983:Q1 to 2007:Q2 (Squares). 68% confidence band of Benchmark period are shaded. Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. 'Cons (NDur+Svc)' is Consumption of Non-durable goods and Services. 'Res' is residential, 'Non-Res' is non-residential, and 'Rel.Price of Inv' is Relative price of investment in terms of consumption.

an increase in investors' risk aversion. They enforce a chilling effect on economic activity and predate a decline in total factor productivity. The results reinforce our initial contention for undertaking this empirical study, which was that FTS shocks have an immediate and long-term negative impact on economic activity esp. Investments. The delayed response of TFP to FTS shocks brings to light the two channels through which FTS impacts the business cycles. Either FTS shock is an over-correction to a speculative bet gone wrong. Or FTS is grounded in rational expectations and represents a risk-aversion shock that induces a re-allocation of capital to safer assets, usually less productive. This increase in pessimism or fear of risk in a sufficient number of agents leads to an imminent long-term decline in economic activity. It is neither the objective nor the scope of this study to decide which of the two expectations channel is more crucial. However, the large and varied set of data included in this empirical exercise and the different assumptions imposed through identification strategies incline us towards the latter.

6.3 Comparison with Shiller data

Comparable series to the Price of Risk series that could account for a part of the term and inflation premium, also have the feature that relative price of safer asset was higher in the 80s and that risk taking has been relatively cheaper in the recent past. For this analysis I additionally consider Robert Shiller's (2015) series which includes:

(A) **LT 10y-earn px:** Long term real excess return (Bond minus Equity) series that adjusts long term nominal yields for growth in CPI,

(B) **TR 10y-earn px:** Total return index (bond minus equity) which compares the price difference between total return real bond index and total return real equity index,

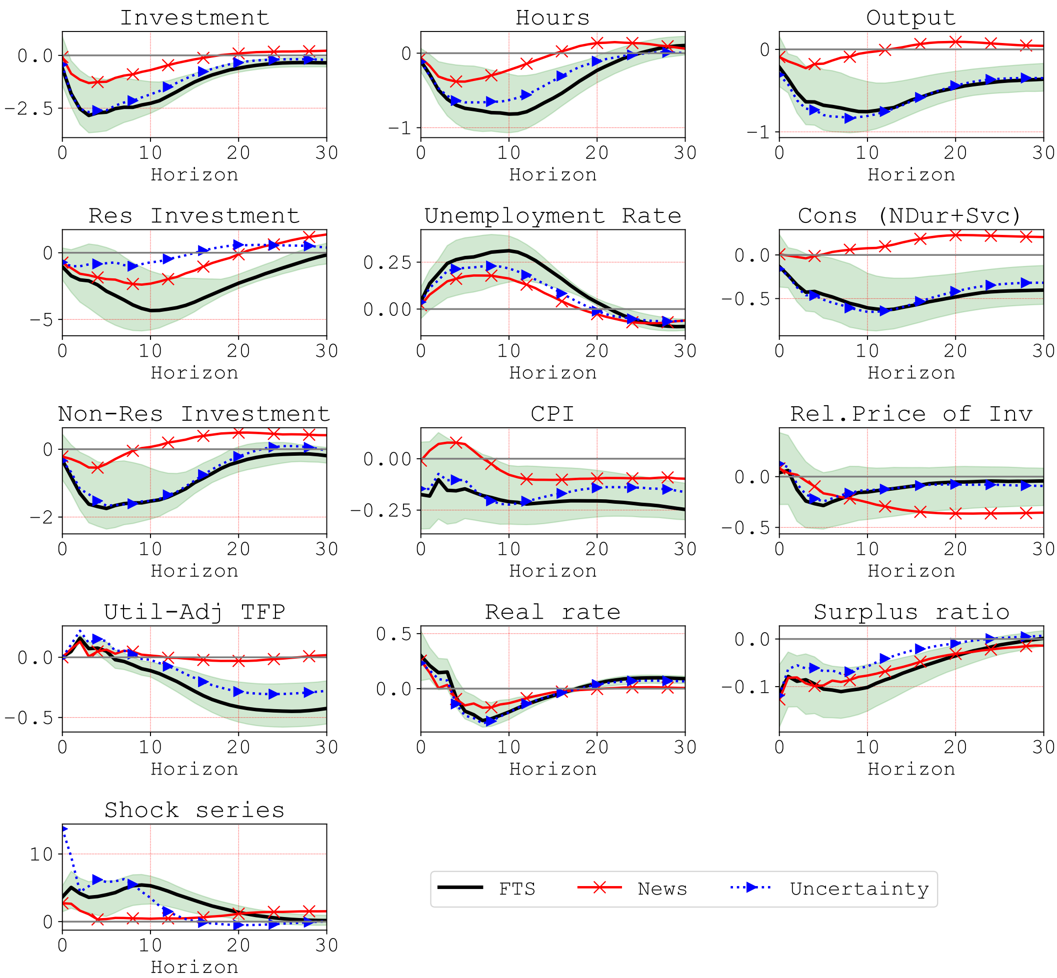
(C) **10y-Cape px:** Excess real bond returns which subtracts the cyclically adjusted price to earnings (CAPE) yield from real bond returns, and

(D) **CAPE:** a series on CAPE itself that has been a hallmark of long term price to earnings ratio.

Additional adjustments[13] are made into these four series to make them compatible

[13]The alternative series from Robert Shiller's database are adjusted as: A. LT 10y-earn px: Log Price difference between assets paying Long-term (LT) 10y yield and LT S&P Earnings

Figure 18: News, Uncertainty and FTS shocks



Notes: Comparison of impulse responses to FTS shocks in benchmark model (Solid) and their 68% Confidence band (shaded) with impulse responses to News shocks (Cross) and Uncertainty shocks (Right arrow). The fourth variable in the benchmark model is 'Price of Risk' and it is replaced with 'Price of Equity' and 'Uncertainty' series to obtain comparable results to the News and Uncertainty shocks. Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock. 'Cons(NDur+Svc)' is Consumption of Non-durable goods and Services. 'Res' is residential, 'Non-Res' is non-residential, and 'Rel.Px of Inv' is Relative price of investment in terms of consumption.

with this chapter' analysis. Of these, the first series (LT 10y-earn px) is the total return series showing a big spike around the global financial crisis (See Figure 28 on page 128). These alternate series using the identification strategy 1 explain around 15-40% of forecast-error variance decomposition which is much lower (See Figure 19 on pages 77 - 78 for comparison) than the 50-60% FEVD decomposition that is explained by the Price of Risk series of this chapter. Of all the 4 Shiller's series that are considered the (LT 10y-earn px) Long term cpi-adjusted bond yield minus long term cpi-adjusted earnings yield series (see fig. 19a) explains the maximum, around 40% of forecast error-variance in investments and related variables. This series is similar in composition to the Price of risk that we have considered in this chapter. Shiller adjusts the long term bond and earnings yield for growth in cpi, like this chapter does it for the Price of risk series, but Shiller's series is only available till 2011, as it adjusts for the long-term future earnings yield of the equity index.

6.4 News, Uncertainty and Risk premium shocks

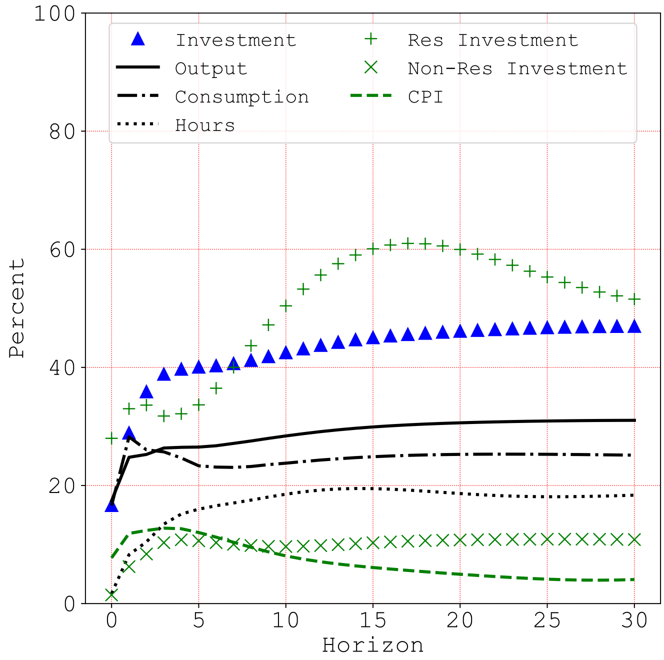
In this section, we check for the robustness of the identification strategy. The analysis starts by looking to answer the criticism that information present in Flight to Safety shocks identified in this chapter is comparable to other News and Uncertainty shocks. Therefore, pursuing the Flight to Safety line of inquiry may not extend our understanding of the business cycle by much. Beaudry and Portier (2006) and Beaudry, Nam, and Wang (2011) uncover the effect of news shocks on the business cycles by identifying news surprises as the shocks to an equity index (S&P 500) series. One of the key results from that analysis is news shocks predate fall in TFP by a couple of quarters. Following their classification of choosing equity index to identify news shocks, we make a comparative analysis in this chapter. The second variable in the benchmark model is replaced from the 'Price of risk' series to S&P 500, and sign and zero restrictions set out in Identification strategy 1 are used to identify 'News' shocks to the latter series.

Similarly, another comparison is made by replacing the 'Price of risk' series in the benchmark model with Bloom (2009) Economic policy Uncertainty (EPU) index, and sign and zero restrictions set out in Identification strategy 1 are used

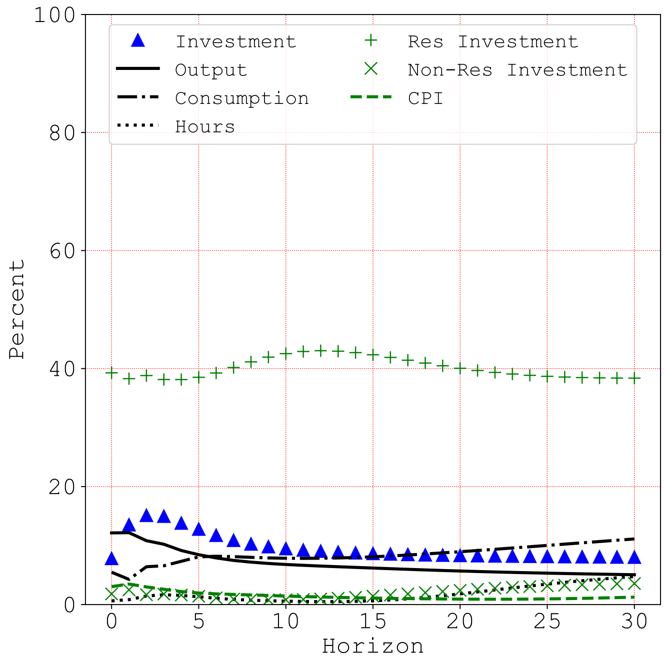
yield, B. TR 10y-earn px: Log Price difference between Total return (TR) 10y bond index and S&P index, C. 10y-Cape px: Log Price difference between assets paying 10y bond yield and Cyclically adjusted S&P Price to Earnings (CAPE) yield, D. CAPE: Log Price of asset paying Cyclically adjusted S&P Price to Earnings (CAPE) yield.

Figure 19: FEVD (%) explained by shocks to alternative Price of Risk series

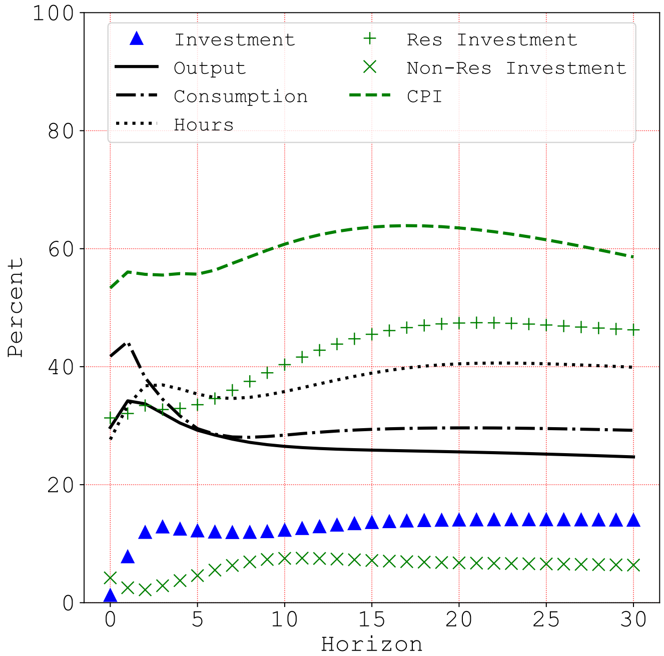
(a) LT 10y yield - Earnings px



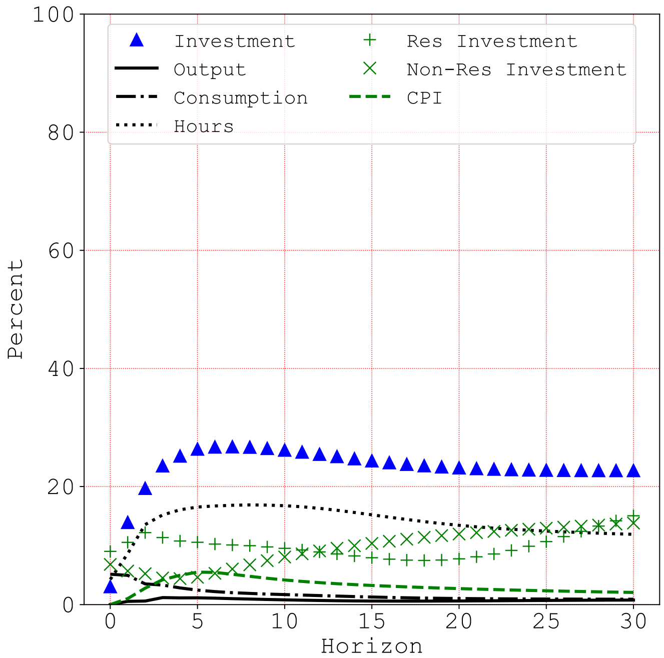
(b) TR 10y yield - Earnings px



Notes: The k-step ahead Forecast error variance decomposition (FEVD %) explained by FTS shocks in series that can act as alternative to Price of Risk series. The alternative series are developed form Robert Shiller's database as: A. Price difference between assets paying Long-term (LT) 10y yield and LT S&P Earnings yield, B. Price difference between Total return (TR) 10y bond index and S&P index, ...continued on next page...



(c) 10y yield - CAPE px



(d) CAPE

Notes (continued):........ C. Price difference between assets paying 10y bond yield and Cyclically adjusted S&P Price to Earnings (CAPE) yield, D. Price of asset paying Cyclically adjusted S&P Price to Earnings (CAPE) yield. The 5 variables in the benchmark model are: TFP, alternative Price of Risk series, Real rates, Surplus Ratio and Investments and it is identified using Sign and Zero restrictions Identification Strategy 1. In other iterations of the 5-variable model, 'Investment' is replaced with other macro variables of interest. The result of 'Investment' and only those variables that replace 'Investment' in the benchmark VAR are reported.

to identify 'Uncertainty' shocks to the latter series.

The impulse response comparison of thus obtained news shocks and uncertainty shocks with the Flight to Safety shocks is made in Figure 18 on page 75.

The careful reader may notice the slight difference in the impulse responses for FTS in Figure 18 with respect to the ones presented in the Results section earlier. This is because the impulse responses in Figure 18 are for the period 1985-2019, which is the entirety of the time period for which Bloom (2009) EPU data is available.

Using only the information present in Equity prices (S&P500) for identifying News shocks, we miss out on much information in the Price of risk series. An impact of that loss of information is visible in impulse responses comparison of News shocks with FTS shocks. The business cycle responses to News shocks are less pronounced and short lived in comparison to the Flight to Safety and Uncertainty shocks. One of the shortfalls of Uncertainty based explanations of business cycle Bloom (2009) is that they have a short-lived impact. The response of business cycle variables to Uncertainty shocks is similar in direction to their response to FTS shocks, but it is significantly short lived and smaller in magnitude for some of the key variables such as residential investments, hours, unemployment, and surplus ratio. The explanatory power of news in Beaudry and Portier (2006) and Beaudry, Nam, and Wang (2011) comes from news disturbances in leading the eventual change in TFP by 2-4 quarters. Through the lens of the identification strategy assumed in this chapter, we see that news shocks have minimal impact on the TFP. As discussed earlier, the FTS shocks lead to decline in the TPF growth rate by 8-10 quarters. From the impulse responses of TFP to uncertainty shocks (in fig. 18), we can say that the median response of TFP to uncertainty shocks is also delayed by 8-10 quarters. This could signify that the uncertainty shocks are an even earlier warning system for TFP decline than FTS shocks. Alternatively, since the magnitude of response of TFP to uncertainty shocks is smaller than its response to FTS shocks, one could counter-argue that it is the latter (FTS) shock that is leading TFP decline through an increase in uncertainty.

Before attributing a lot of the explanatory power to uncertainty shocks, we must also consider that the Economic policy uncertainty index (EPU), which measures uncertainty shocks, is back-calculated by counting policy uncertainty related words in news articles (Bloom, 2009). The EPU index already accounts for most of the speculation and expectation feeding into the TFP decline and

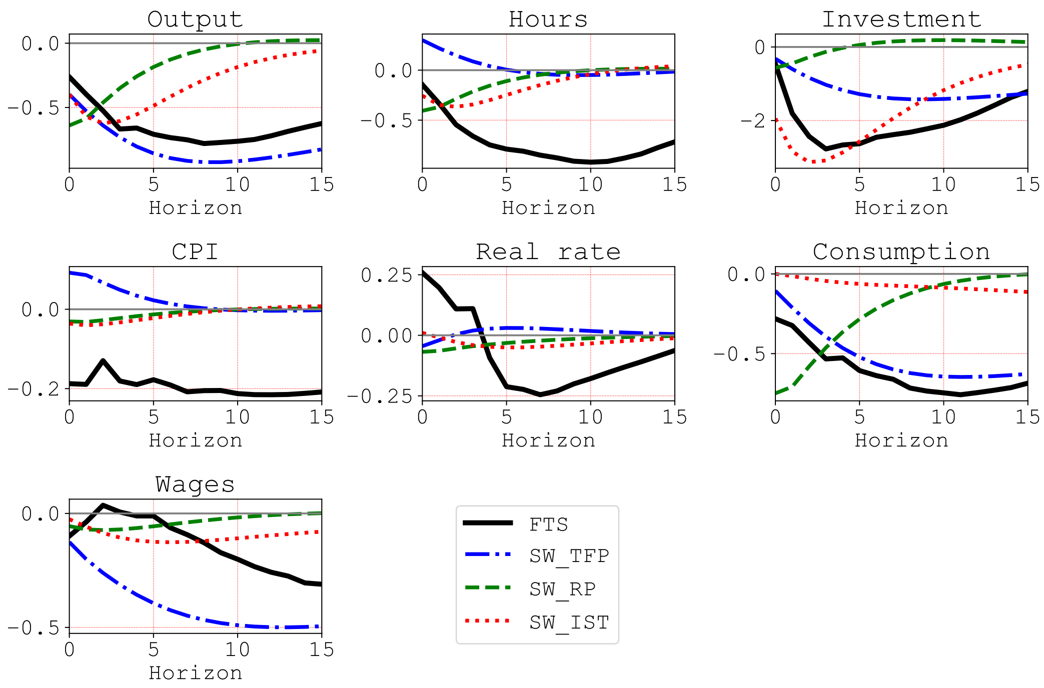
Flight to Safety. There is a significant overlap between these, and the impulse responses in Figure 18 may not be sufficient to resolve this confusion. So I use the Granger-causality test [See Table 5 on page 80] for identifying the lead-lag relation between FTS and Uncertainty shocks. The exercise shows that the Price of risk series, responsible for FTS shocks, Granger causes Uncertainty series at lags 2-3 while the Uncertainty series does not Granger cause the Price of risk at those lags. It demonstrates a lagged relationship between the two where the long-run impact of the Uncertainty shocks on TFP is a derivative of lagged FTS shocks.

Table 5: Granger Causality results for FTS shocks

A. Does lagged 'Price of Risk' series Granger cause any of these variables							
lags	EPU	S&P 500	1y-10y	Baa-Aaa	TFP	TFP(EqDur)	Inv Share
1	0.658	0.709	0.134	0.09	0.017*	0.001**	0.865
2	0.016*	0.82	0.05*	0.0**	0.022*	0.002 **	0.96
3	0.048*	0.0**	0.101	0.002**	0.048*	0.008**	0.94
4	0.091	0.0**	0.067	0.003**	0.056	0.009**	0.57
5	0.146	0.0**	0.063	0.007**	0.087	0.006 **	0.657
6	0.063	0.0**	0.045*	0.002**	0.154	0.011*	0.586
7	0.121	0.0**	0.126	0.004**	0.136	0.022*	0.69
8	0.121	0.0**	0.135	0.005**	0.121	0.031*	0.67
12	0.207	0.0 **	0.18	0.009**	0.223	0.083	0.403
B. Does any of these lagged series Granger cause 'Price of Risk'							
lags	EPU	S&P 500	1y-10y	Baa-Aaa	TFP	TFP(EqDur)	Inv Share
1	0.334	0.713	0.28	0.236	0.579	0.478	0.695
2	0.081	0.432	0.159	0.323	0.277	0.131	0.718
3	0.062	0.494	0.281	0.263	0.063	0.007**	0.802
4	0.11	0.568	0.348	0.355	0.086	0.011*	0.831
5	0.202	0.571	0.034*	0.446	0.091	0.011*	0.864
6	0.166	0.631	0.07	0.546	0.014*	0.025*	0.605
7	0.151	0.795	0.046*	0.756	0.023*	0.033*	0.748
8	0.185	0.804	0.055	0.282	0.051	0.067	0.758
12	0.649	0.38	0.19	0.35	0.113	0.247	0.666

Notes: p-values are reported. * signifies 95% confidence, ** signifies 99% confidence. EPU: economic policy uncertainty index. 1y-10y: liquidity spread between 1 year and 10 year yields. Baa-Aaa: corporate bond spread. TFP(EqDur): TFP in Equipment and Durables consumption. Inv Share: equipment and consumer durables share of total output.

Figure 19: Comparison with Smets & Wouters (2007)



Notes: Comparison of median impulse responses to FTS shocks from Benchmark model (Solid) with updated (to 2019:Q3) results from Smets and Wouters (2007) model. SW_TFP is negative shock to TFP (Dash-dots), SW_RP is positive shock to Risk Premium, and SW_IST is negative shock to Investment-Specific Technology. Y-axis label is percentage points and X-axis label is Time (in quarters) horizon after the shock.

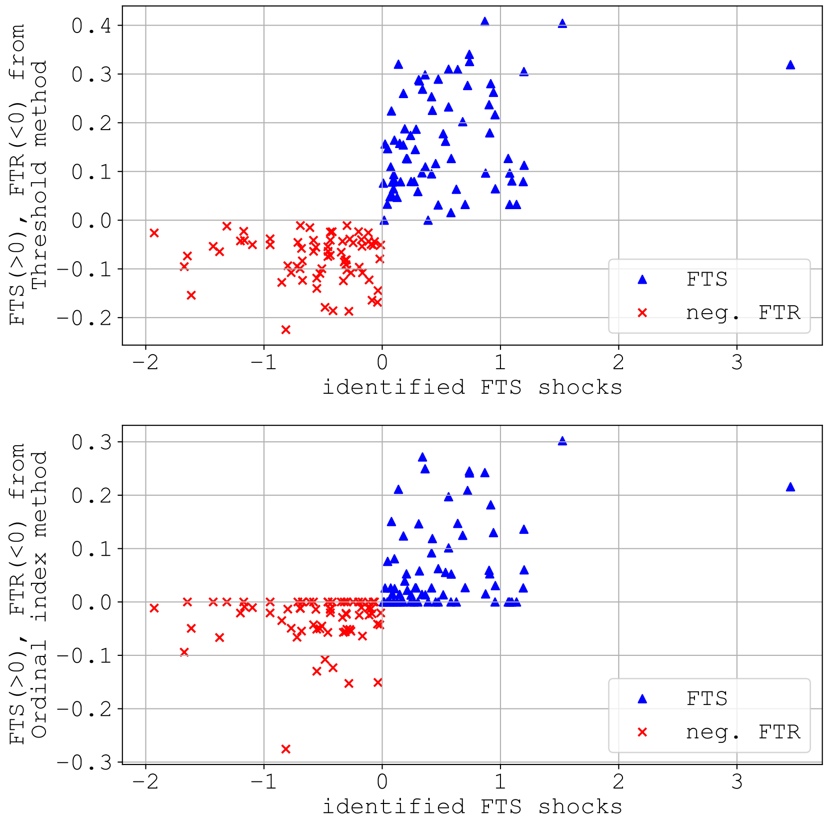
The Granger causality relationship of Price of Risk to News shocks, estimated from the S&P 500 series, is even stronger in comparison and runs to 12 lags. Table 5 on page 80 also reports Granger causality results from FTS to time-series, which are similar to the Price of risk developed in this chapter in containing information about Flight to Safety and which have been explored in literature for capturing sentiments and uncertainty about investments. These are liquidity spread between 1-year and 10-year yields (1y-10y), corporate bond spread (Baa-Aaa), TFP total, TFP in Equipment, and Durables consumption [TFP(EqDur)] and equipment and consumer durables share of total output (Inv Share). There is significant Granger causality running from the Price of Risk series to these alternate series. None of the series except for TFP in Equipment and Durables consumption [TFP(EqDur)] series Granger causes the Price of risk, and even for TFP(EqDur) series, the Granger causality is significant for lags greater than 3. However, the Granger causality running from the Price of risk is significant even for shorter lags.

In Figure 19, the findings of this chapter are compared with the established results from workhorse DSGE models equipped with investment technology and risk premium shocks (Smets and Wouters, 2007). The impulse response impact of adverse shocks to TFP, negative shocks to investment-specific technology, and positive shock to risk premium in an updated 2019 model version of Smets and Wouters (2007) are slow and less severe when compared with the impulse responses to FTS shocks studied in this chapter. The impulse responses to Smets and Wouters (2007) model also have the typical macroeconomic puzzles, such as a negative correlation of output, consumption, and investment with hours, which the results from the FTS shocks identified in this chapter seem to avoid.

The identified shocks from the benchmark configuration compare well against the FTS and FTR obtained by alternate methods such as the Ordinal index approach and the Threshold approach (Baele, Bekaert, Inghelbrecht, and Wei, 2013). Comparing the two methods with the identified shocks to the Price of risk series of the benchmark VAR is made through scatter plots in Figure 20 on page 83. It shows two interesting phenomena. Firstly, that during the (quarterly) periods when the VAR identifies a positive shock to the Price of risk series, there is also a higher likelihood of FTS days in those periods. And secondly, the likelihood of Flight to Safety days is higher than Flight to Risk days' likelihood. Obviously, the measure of FTS and FTR likelihood, which are calculated using Threshold (Appendix B.2) and Ordinal index (Appendix B.3) method are dependent on the selected parameter (κ or k), and a higher choice of that parameter would limit the likelihood of observing the extreme flight of capital in either direction (towards risk or safety). For the purpose of this analysis, it is important to note that in the Threshold method, the κ is chosen to be equal to 1, which results in 11% of total days being classified as FTS, and in the Ordinal index method, a choice of k is also equal to 1 gives 3.4% FTS days. Detailed methodology of finding the FTS and the FTR days using the two methods is made in this chapter's Appendix B.1. A comparison of FTS and FTR days using the ordinal index method with k of 1, as shown in Figure 26 on page 126, also provide us more significant and more frequent spikes during FTS days than during FTR days.

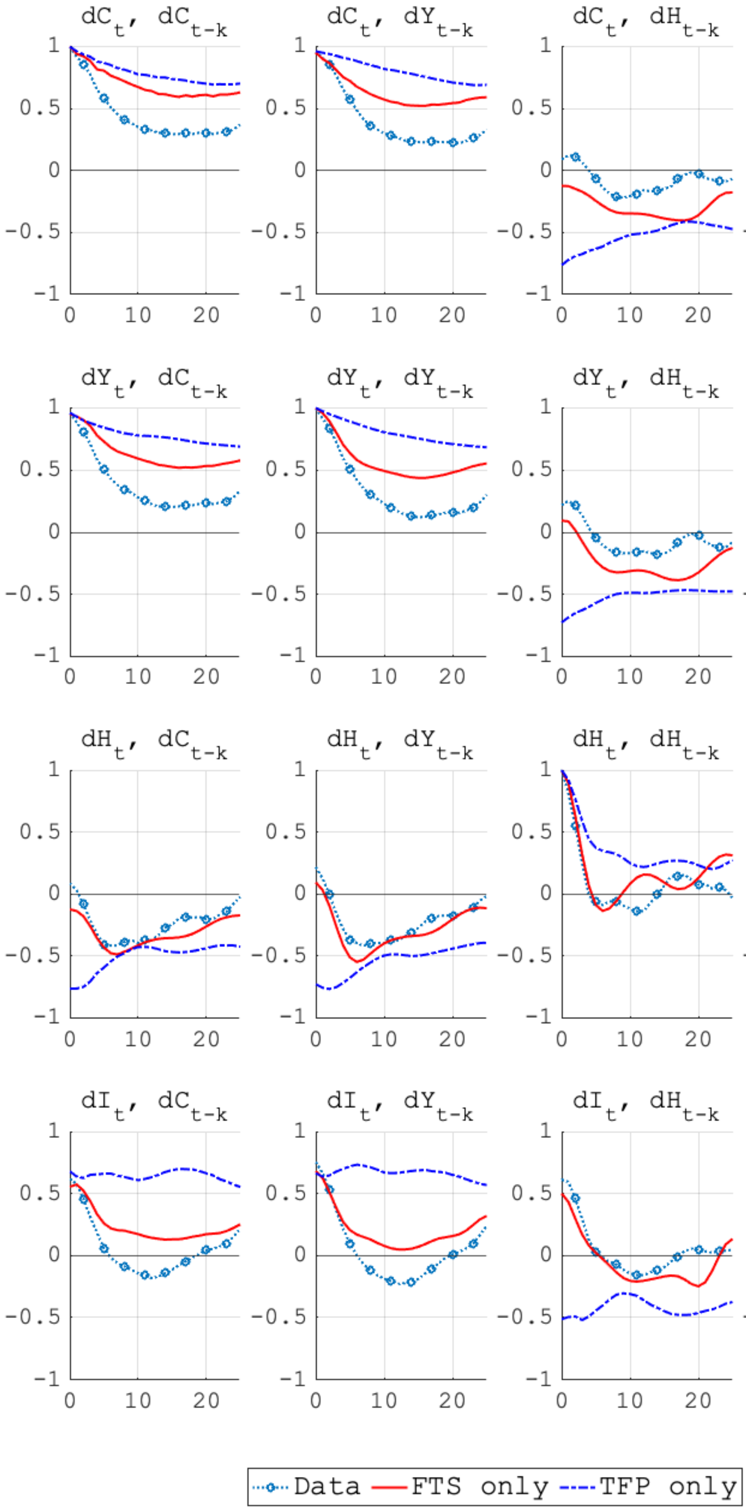
Lastly, we take a look at the correlation between the obtained shocks and the data, which is presented in the correlogram [See Figure 21 on page 84]. This investigation shows that the benchmark model fitted with only FTS shocks captures most of the correlation in data, which the model fitted with TFP shocks only fails to do.

Figure 20: FTS/FTR from Threshold and OI method



Notes: Scatter plot comparing the median structural shocks to price of risk series from benchmark VAR for period 1983:Q1 to 2019:Q3 (X-axis) with Quarterly average of FTS probability and negative (neg.) of FTR probability values (both on Y-axis). The FTS and FTR are calculated using Threshold method with $\kappa = 1$ in top figure and are calculated using Ordinal index method with $k = 1$ in bottom figure. The calculations are discussed in detail in Appendix B.1. FTS are only reported for quarters when identified shocks were positive, while negative (neg.) of FTR are only reported for quarters when identified shocks were negative.

Figure 21: Correlogram of Data and Model with FTS and TFP shocks



Notes: Y-axis: Cross-Correlation of the growth rate of Consumption (dC), Output (dY), Hours (dH) and Investment (dI) in US Data and the benchmark model fitted with only Flight to safety (FTS) shocks and TFP shocks identified using Sign and Zero restrictions discussed in Strategy 1. X-axis: k lag lengths.

7 Discussion

Our understanding of macroeconomic shocks and their propagation has come a long way since the early days of C. A. Sims (1980a) and Kydland and Prescott (1982). Most of the US business cycles' features have been well established in the Real business cycle literature. Ramey (2016) has a detailed discussion on this topic. The key results are that consumption is less volatile than output, output is less volatile than investment, but output is similarly volatile to hours. The US macroeconomic data series also shows co-movement and pro-cyclicality (J. H. Stock and Watson, 1999). However, not so well established in the RBC literature is the role of asset prices and the causes of business cycles (Rebelo, 2005).

The standard neoclassical paradigm of real business cycle models cannot rationalize the high expected risk premium observed in the US equity market returns or the low risk-free rate in US bond returns. It has resulted in puzzles [for e.g. Mehra (2003) and Donaldson and Mehra (2007) evaluate attempts to resolve the 'Equity premium puzzle' since it was first introduced in Mehra and Prescott (1985)].

With regards to our understanding of the nature and cause of business cycle fluctuations, much progress has been made through structural vector autoregressions and DSGE based research, but the literature is still inconclusive. This section discusses the developments of the last two decades in explaining business cycle fluctuations from the perspective of technology shocks, investment-adjusted technology shocks, the marginal efficiency of investment shocks, financial shocks, news shocks, information shocks, risk shocks, and uncertainty shocks, and compares them in light of the results from FTS shocks, as identified in this chapter.

7.1 Neutral Technology shocks

The usual explanations for the cause of business cycles for a long time were policy (monetary and fiscal) shocks and cost shocks. Kydland and Prescott (1982) added technology shocks to the list, and the literature that followed controversially attributed the cause of recessions to a fall in total factor productivity. These technology shocks raised productivity in all factors of production (labour and capital), which is why they are also known as neutral technology shocks.

Galí (1999) fuelled the opposition to this thought of understanding recessions as periods of technological regress. By identifying technology shocks as the only source for long-term labor productivity changes in his model, he could show that 'hours' at least in the short run fell in response to technology shocks. King and Rebelo (1999) and Baxter and King (1999) defend the RBC models by showing pro-cyclicality of hours to output. Francis and Ramey (2006) reconstruct the US historical data from WWII to find that technology shocks in later periods only raise productivity gradually, and this gradual rise provides an inventive to reduce hours in short-run for the anticipation of increasing hours in response to higher productivity in the long-run. Like Galí (1999), Francis and Ramey (2005), too, assume that hours have a unit root, and they show that their results are robust to over-identification tests.

Nevertheless, the assumption of considering a unit root in hours per capita is criticized by Christiano, Eichenbaum, and Vigfusson (2003), and they find that Gali's results fail if hours are used in levels instead of first-differences. Chari, Kehoe, and Mcgrattan (2000) dispel Gali's findings as being driven by measurement error. By bringing additional methods Basu, Fernald, and Kimball (2006) defended Gali's results. They use hours per worker as a proxy for making utilization adjustment to the Solow residual. This series is regularly updated and made available online [see Fernald (2012)]. Shocks to this adjusted series lead to a reduction in hours worked. In contrast, the vector autoregressions approach by Alexopoulos (2011), using a new series based on books published in the field of technology, finds that positive technology shocks lead to an increase in total factor productivity, investment, and to an extent, hours. Unsettled, the debate moves on to look for alternative explanations for business cycle fluctuations.

7.2 Investment-specific technology and MEI shocks

A prime alternative explanation to technology shocks is raised in investment-specific technology shocks (IST). As the name suggests, the investment-specific technological productivity shocks raise the productivity of only new capital (investment goods). The impact of a positive investment-specific technology shock (IST) is visible in the price of additional investment, becoming lower in terms of the price of consumption goods. It also increases the real rate of investment.

J. Greenwood, Hercowitz, and Krusell (1997) and (2000) were the first to examine the marginal efficiency of investment (MEI) shocks and the investment-specific technology (IST) shocks in calibrated DSGE models. They found them to account for around 30% of the variation in output. Over the last decade, several influential papers have argued that IST and MEI shocks are the key drivers of business cycles. See Fisher (2006) for long run restrictions VAR, Altig, Christiano, Eichenbaum, and Lindé (2011) for structural VAR, Justiniano et al (2010, 2011) for DSGE model and Araújo (2012) for emerging markets based evidence. Fisher (2006) extends Galí (1999) by assuming that only IST shocks impact relative price of investment and finds these shocks to explain more than 60% of variation in output growth and hours. Bernanke, Gertler, and Gilchrist (1999) establish the role of credit frictions in investment-specific technology shocks.

In models with an RBC core Barro and King (1984) conjecture (or curse) that only technology shocks can account for the observed co-movement among output, consumption, investment, and hours. They conjecture that after a positive investment (IST or MEI) shock, there would be a tendency to raise investment much higher than could be afforded by increasing labour effort. Therefore, any difference between labour income and investment would have to be made up by reducing consumption. This fall in consumption runs against the evidence of pro-cyclicality of consumption with output in data. Therefore investment shocks cannot be the primary driver of business cycles in models with inseparable preferences and an RBC core. Justiniano et al (2010, 2011) overcome this curse by including nominal and real rigidity in their model. Other researchers too, such as Khan and Tsoukalas (2011), J. Greenwood, Hercowitz, and Krusell (2000), Furlanetto and Seneca (2014) have extended their models with capital utilization cost, non-separable preferences, habits persistence, adjustment costs in intermediate inputs and investments adjustment costs. Such extensions introduce some form of real rigidity in their models to generate an explanatory power for investment shocks.

Medium scale DSGE model of Smets and Wouters (2007), on the one hand, confirms that productivity shocks have a negative short-run impact on hours worked. This is consistent even for a flexible price economy as argued by Galí (1999). However, on the other hand, they also raise doubts about the significance of investment-specific technology shocks. 'Demand' shocks, which in their model are captured via risk premium shock, exogenous spending, and investment-specific technology shocks, explain significant variation in macro data but only in the short-term. Whereas, only technology shocks explain most of the long-term variation in data.

In contrast, results from DSGE models of Justiniano, Primiceri, and Tambalotti (2010) and (2011) show that investment shocks are the primary driving force in output fluctuations. Their source of discrepancy with Smets and Wouters (2007) results from the different ways in which they measure investment and consumption in their models. They include durable goods consumption and inventories into Investments. Consumption of durables goods has also been commonly included in the definition of investments by other estimated DSGE models [See, Cooley and Prescott (1995), Christiano, Eichenbaum, and Vigfusson (2003) and Del Negro, Schorfheide, Smets, and Wouters (2007)]. Whereas, the Smets and Wouters (2007) model, unlike Justiniano, Primiceri, and Tambalotti (2010) and (2011), does not include inventories in investments but includes purchases of consumer durable goods in consumption. Both durable goods consumption and inventories are the more cyclical components of GDP (J. H. Stock and Watson, 2016) and including durable goods consumption and inventories in investment makes that investment series more volatile and procyclical.

Justiniano, Primiceri, and Tambalotti (2010) argue that it is the first of the two changes they make that is significant in driving their results. The first change they make to Smets and Wouters (2007) is by excluding durables goods from consumption and including them into investment. This change is majorly responsible for the increase in the variance decomposition at the business cycle frequency, which is explained by the investment-specific technology shock in their paper compared to Smets and Wouters (2007). Whereas in the case of the second change, when Justiniano, Primiceri, and Tambalotti (2010) exclude inventories from investment and move their investment series closer to Smets and Wouters (2007) definition of investment, it leads to two changes. First, the investment shock parameter becomes large, dampening investment shocks' impact on investment, output, and consumption. Second, the preference shock has less impact as there is a weaker response from both output and consumption.

The understanding from investment and the marginal efficiency of investment based literature is that investment-specific technology shocks explain most of the variance in output at business cycle frequency. However, the case for investment shocks as a significant contributor to business cycles, as shown in the significant result of Justiniano, Primiceri, and Tambalotti (2010) and (2011), seems less convincing if we include financial frictions in the model.

7.3 Financial frictions and Risk shocks

The rate at which investment goods are converted into consumption goods is identified as the main driver of business cycles, but this rate of change is controlled by the investment adjustment cost parameter in investment-specific technological shocks models, such as Justiniano, Primiceri, and Tambalotti (2011). Investment shocks are also linked to financial markets, and frictions in financial markets determine the pace of conversion of investment goods into consumption goods. Kamber, Smith, and Thoenissen (2015) exploit this feature by introducing a collateral constraint (Kiyotaki and Moore, 1997) into Smets and Wouters (2007) type of model and demonstrate that the ability of positive investment shocks in raising entrepreneurial consumption is attenuated in the presence of collateral constraints.

In the presence of binding collateral constraints, investment shocks' ability as a key driver of business cycles is diminished, and identification of robust investment specific structural shocks in DSGE models is difficult as per Kamber, Smith, and Thoenissen (2015). They also show that with investment shocks, there is no co-movement between consumption and output, going back to the original argument of Barro and King (1984). A positive investment shock lowers the relative price of investment goods, Tobin's Q. When the collateral constraint is binding, the entrepreneur, due to a positive investment shock, loses her collateral value. An increase in borrowing cannot finance a further increase in investment. Therefore, the binding collateral constraint stalls entrepreneurs' borrowing ability, and additional investment can only be made by reducing entrepreneurial consumption.

Risk shocks replace the role of investment shocks in explaining the variance in output data once borrowing constraints are included (as in Kamber, Smith, and Thoenissen (2015)). Their estimated risk premium shock rises sharply at the beginning of each post-war recession. The effective interest rate, as in Kamber, Smith, and Thoenissen (2015) is highly counter-cyclical. In the presence of a favourable risk shock, they find that there is an increase in investment demand. A negative risk premium shock lowers households and entrepreneurs' interest cost, even for those investors for whom the borrowing constraint is binding. This reduction in borrowing rates and lower debt-service cost allows them to undertake additional capital purchases simultaneously, raise their consumption, and avoid the co-movement puzzle of consumption not being pro-cyclical with output. An increase in Tobin's Q following a favourable risk shock loosens the borrowing constraint and further amplifies this mechanism. In this manner, we can see that as financial frictions are included, the significance of Investment specific technology shocks is reduced, and that of risk premium shocks is improved.

Similar mechanisms in Christensen and Dib (2008) and Merola (2015), which include an external finance premium that is impacted by firms' net worth, suggest that the variance decomposition contribution of Investment specific shocks is reduced in the presence of financial frictions. In a related paper, Nolan and Thoenissen (2009) describe that shocks to the financial sector in the form of entrepreneurial net worth play a significant role in business cycles, much more than TFP or monetary shocks, and these shocks are negatively correlated with external finance premium. Equity payouts are pro-cyclical, while debt payouts are countercyclical for US firms, as studied by Jermann and Quadrini (2012). They also show that events originating in the financial sector end up tightening firms' financing conditions and are quantitatively crucial in explaining the dynamics of real and financial variables and contributing to the great recession of 2007-08. Amano and Shukayev (2012) show that risk premium shocks are particularly important in driving the economy to ZLB.

DSGE model in Christiano, Motto, and Rostagno (2014) through agency problems of asymmetric information and costly monitoring (like Townsend (1979) and Bernanke, Gertler, and Gilchrist (1999)) introduces idiosyncratic uncertainty to the way entrepreneurs can convert raw capital into useful capital. Entrepreneurs pay a premium to borrow capital. This premium represents the riskiness of bet on each entrepreneur. By estimating their model using macroeconomic and financial variables, they conclude that shocks to the volatility of idiosyncratic uncertainty or risk shocks account for most fluctuations in GDP at business cycle frequency. The risk shocks-based view of business cycles is compelling; however, in DSGE models without some form of financial frictions, it gets challenging to disengage between risk shocks and the marginal efficiency of investment shocks.

7.4 News and Uncertainty shocks

The hypothesis that future technology expectations play an important role in driving business cycles was formalized in Beaudry and Portier (2004). By using stock prices as the basis for forming expectations about future economic conditions and by using two sequential identification schemes; first which makes innovations to stock prices orthogonal to TFP shocks, and second which drives the long term movement in TFP, Beaudry and Portier (2006) demonstrate that their news-driven shocks anticipate TFP growth by a couple of years. Beaudry and Portier (2005), Beaudry and Lucke (2010), Beaudry, Dupaigne, and Portier (2011) reach similar conclusions. Jaimovich and Rebelo (2009) in a DSGE model further posit that news shocks about economic fundamentals generate comovement in aggregate productivity and account for comovement in sectoral productivity as well. However, in a different VAR scheme by identifying news shocks as orthogonal to technology innovation and one which maximizes future variation in technology, Barsky and E. R. Sims (2009) show that the positive wealth effect generated from positive news about future productivity cannot lead to an expansion in RBC models. The increase in consumption and leisure from the wealth effect leads to a fall in output and hours. Suppose instead, because of the high elasticity of intertemporal substitution, the real rate of return effect dominates. In that case, investment and hours increase, but the increase in output does not compensate for the increase in investment, and so consumption falls.

The strength of the news-driven business cycle is also challenged when considering the significant relation between periods of economic downturn and high uncertainty. The volatility of the stock market or GDP is an often-used measure of uncertainty. This volatility surges during recessions. However, this surge cannot be explained by a measure of bad news or an increase in risk aversion (during recessions) alone. Only 1 of the 17 instances of volatility jumps from 1962 to 2008 that lowered the expected GDP growth and led to an increase in economic uncertainty was due to 'bad news' (Bloom, 2009). It is not surprising then that the macroeconomic research since the Global financial crisis has emphasized considering uncertainty, volatility, information, and sentiment-based shocks to understand the business cycle fluctuations.

On the one hand, uncertainty negatively impacts growth and spending. Romer (1990) says uncertainty near the Global Depression is responsible for a fall in durable consumer spending. In an influential paper Bloom (2009) depicts the cyclical variation in the standard deviation of firm-level stock returns, which he calls as uncertainty, to be an important determinant of business cycles. Uncertainty results in cautious decision-making on behalf of firms, as they deliberate on hiring and investment decisions since adjustment costs make those decisions expensive to reverse. It also results in cautious decision-making on behalf of consumers, as during high uncertainty, they delay consumption, especially of durable goods. Both these responses also reduce the efficacy of monetary and fiscal policy.

On the other hand, negative growth creates uncertainty. Period of negative growth, or recessions, also raise uncertainty by slowing down trading activity, difficult forecasting ability, policy miscommunication, and hyper-activism. Baker, Bloom, and Davis (2016) show that due to slackness in business activity, there is an increase in micro-level uncertainty since businesses try out new ideas for the reason that they are now cheaper to try. Nakamura, Sergeyev, and Steinsson (2017) using consumption and growth data from 16 OECD countries find that periods of lower growth have high fluctuations in long-run volatility. Income and wages, especially for low-wage earners, show volatility surge during recessions.

Contrary to traditional business cycle models (Kydland and Prescott, 1982), the uncertainty based results from Bloom (2014) and Baker, Bloom, and Davis (2016) further provide evidence that a fall in productivity is an effect of an increase in uncertainty, rather than a response to technological regress. They find that increase in uncertainty has a chilling effect on the productivity-enhancing reallocation of high productivity and low productivity firms. As uncertainty increases, high productivity firms do not want to be aggressive in their productivity allocation, and low productivity firms do not want to cut back on their aggressive propositions. We know that the reallocation of resources tends to drive most of the observed productivity growth. Therefore this hiatus in productivity reallocation during high uncertainty stalls productivity growth and such a stalling effect of uncertainty underlies the theory of uncertainty driven business cycle.

Uncertainty driven business cycle hypothesis finds support from micro-level evidence of Panousi and Papanikolaou (2011), which discusses the impact of CEO level decision making from an increase in uncertainty. CEOs do not make risky investments if their net worth is tied to or highly exposed to the firm's equity valuation and its risk valuation. The structural model in Bloom (2014) estimates that an average uncertainty shock has reduced the GDP by 1.3%. The uncertainty after the great recession was thrice as compared to previous uncertainty shocks. So around 3-4% of the fall in GDP during GFC could be attributed to uncertainty. A sudden increase in uncertainty due to natural disasters, terrorist events explain about 50% of the variation in output (Baker, Bloom, and Davis, 2016) following the event.

Arguably, the business cycle impact of uncertainty is limited only for the short term (Bloom, 2014). In the short run, investment and output reduce, but as uncertainty is reduced and once pent-up demand increases, an increase in hiring and investment leads to a rebound. Similarly, L. Stein and Stone (2010) show uncertainty accounts for a third of the fall in capital investment during 2008-10. However, uncertainty also seems to increase spending in R&D. Many new ventures are undertaken in uncertain times because there are more avenues for growth but less certainty about which avenues would be successful. The surge in R&D activity in 2020 to devise a vaccine that could eradicate the Covid-19 virus is one example.

7.5 Reconciling Business cycles with Flight to Safety

In a nutshell, various attempts undertaken over the past three decades to explain the co-movement in macroeconomic variables through business cycles have been successful in some parts. They have led to inconsistencies and puzzles in others. Neutral technology shocks explain most of the fluctuations for output and consumption but do not account for their co-movement with hours. Investment-related technology shocks using real frictions in the transformation of raw capital into meaningful capital can break the Barro-King (1984) curse, explain most of the output fluctuations, and reconcile hours to business cycles, but the results diminish in the presence of financial frictions. Agency cost, collateral constraints, asymmetric information, and risk-based models explain co-movements in business cycles. However, there is difficulty in specifying structural shocks robust to modest changes in these financial frictions. Expectations and uncertainty shocks are promising indicators of the future economic climate and driving economic fluctuations, but their impact on business cycles is mostly limited to the short run.

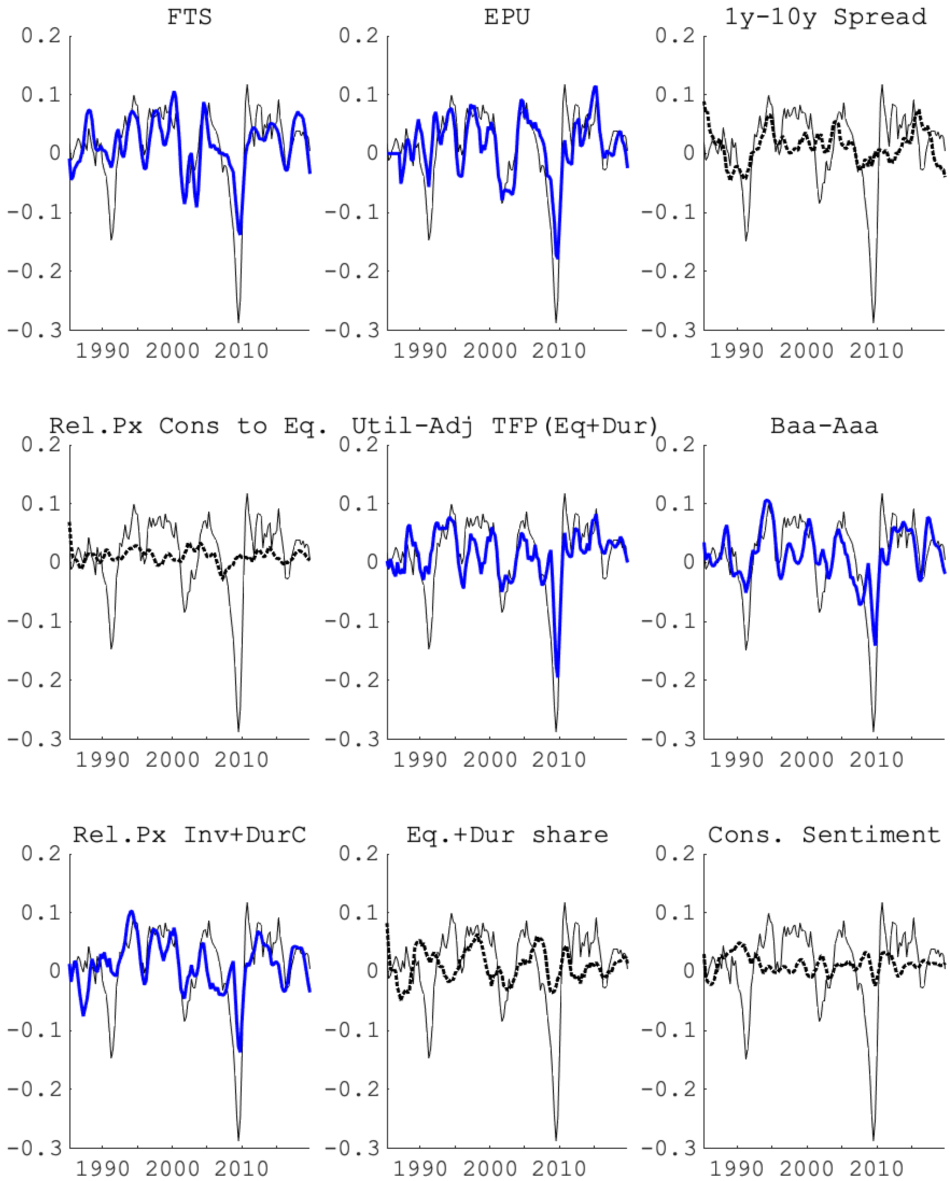
As presented in this chapter, the research on business cycles showcases - Flight to Safety - shocks as the major driver of economic fluctuations in the long run. There is a striking similarity between an increase in uncertainty and Flight to Safety. An increase in uncertainty leads to precautionary savings, which reduces consumption (Bansal and Yaron, 2004) and leads to Flight to Safety. Some of this increase in savings also flies abroad, as Fernández-Villaverde et al. (2009) show that an increase in uncertainty can lead to a flight of capital from small and open economies to larger and more closed ones, such as the United States. Greater uncertainty leads to higher default risk, an increase in risk premia, and makes ambiguity averse investors (Hansen, Sargent, and Tallarini, 1999) act as if the worst possible outcome is expected to occur. If uncertainty led expectations are the key drivers of investment rationale and business cycles fluctuations, then one mechanism where the impact of uncertainty is immediately reflected is FTS.

Measures of uncertainty developed in the last decade are at best proxies of the central phenomenon; one additional potent measure to that list could be FTS. Figure 22 on page 95 describes the growth of US investment series that can be explained by shocks to other comparable series. These alternate time-series are similar to the Price of risk developed in this chapter in containing information about Flight to Safety and which have been explored in literature for capturing sentiments, uncertainty, and risk aversion pertaining to investments.

The thick solid lines in that figure represent variables that closely resemble the contribution to Investment growth made by FTS shocks. Shocks to investment-related variables series that are used in investment-specific TFP shocks literature, such as the TFP in Equipment and Durables consumption [TFP(EqDur)], and the Relative price of Investment and Durables Consumption to price of Consumption of Non-Durables and Services (Rel.Px Inv+DurC). These shocks exhibit higher contribution to deviation in investment growth. In comparison shocks related to consumer sentiment and liquidity spread between 1-year and 10-year yields (1y-10y) show lower contribution. There is also a similarity in results from the corporate bond spread (Baa-Aaa) and economic policy uncertainty (EPU) as both these series reflect the impact of Flight to Safety. The significant Granger causality (which we have already noticed in table 5 on page 80) running from Price of Risk series to these alternate series reassures the faith in pursuing Flight to Safety as germane to understanding the nature of business cycles.

The main finding of this paper is to show that Flight to Safety has a long term impact on the economy. Flight to Safety shocks can also provide additional fillip of generating a long-term impact on the economy, which is missing in the uncertainty based literature. It would be interesting to establish the relevance of Flight to Safety through an estimated DSGE model, which has a safe and risky investment technology and a precautionary mechanism for investors to allocate between those two. That would be a fascinating avenue for future research.

Figure 22: Contribution from sentiment variables



Notes: Investment growth in data (thin solid line in all charts, %y/y) in comparison with the investment series fitted with shocks identified from Sign and Zero restrictions discussed in Strategy 1. Data: 1985:Q1 to 2019:Q3. The benchmark configuration of the model identifies 'FTS' shocks as disturbances to 'Price of Risk' series. In other iterations of the model this is replaced with other interesting proxies for consumer expectations/sentiment and results from shocks to that replacement series of interest are reported. Such as: 'EPU' is Baker, Bloom and Davis (2016) Economic Policy Uncertainty index. '1y-10y spread' is liquidity spread on US 1 year and10 year T-bills. 'Rel.Px Cons to Eq.' is Relative price of Consumption to price of Equipment. 'Util-Adj TFP (Eq+Dur)' is the Utilisation-adjusted TFP in producing Equipment and Consumer Durables. 'Baa-Aaa' is the spread on corporate bonds rated Aaa and Baa. 'Rel.Px Inv+DurCons' is the Relative price of Durables Consumption and Investment to Consumption of Non-Durables and Services. 'Eq.+Dur' share is the share of Equipment and Consumer Durables to Output. 'Cons. Sentiment' is US Consumer Sentiment indicator.

8 Summary and Conclusions

This chapter's central conviction is to identify the role of Flight to Safety as the critical driver of business cycle fluctuations. It achieves so by using a Price of risk series that measures the price differential of a safe and risky asset in a five variable structural vector autoregressions model identified using Uhlig (2005) sign based restrictions. The results show that Flight to Safety shocks predate any regress in total factor productivity by several years. Flight to Safety shocks can account for more than 50% of fluctuations in macroeconomic variables at business cycle frequency. This analysis is robust to small alterations in the identification strategy and excluding the post-Global financial crisis period data from this investigation. FTS shocks have gained a more prominent role in the past three decades as expectations formation, and policy communication has improved in that time.

Flight to Safety shocks lead to a long and sustained decline in investment-related macroeconomic variables, the mechanism with which they can achieve so asks several questions from the established tenets of business cycle dynamics. Various business cycle researchers at different stages have posited neutral technology, investment-specific technology, financial frictions, among others, as the main reason for economic fluctuations. Recently there is a focus on looking at expectations formation, in the form of news shocks and uncertainty shocks, as the main drivers of business cycles. This chapter proposes an alternative view that shocks to investor risk aversion lead to booms and busts in business cycles.

A typical FTS episode is signified by a sudden increase in appetite for safe assets with respect to risky investments. The notion that during times of uncertainty, economic agents change their behaviour, by exhibiting caution towards consumption and increasing their savings is quite old and one of the defining reasons for the study of macroeconomics. How FTS shocks impact the long term fluctuations in business cycle variables inclines us to support the view that Flight to Safety works through the *Expectations channel*. Rational, risk-averse investors, in response to an increase in uncertainty about their future income and employment, exhibit precautionary behaviour to increase savings today to smooth out their consumption path and alleviate the impact of realization of a bad state in the future. Investors smooth their consumption by shifting long term savings from risky to safer assets. Such a shift by a large number of people leads to a drop in macroeconomic activity that is visible through a fall in output, investment, productivity, hours, consumption, and in a broader economic gloom.

One of the primary motivations for pursuing this empirical exercise was searching for explanations for the unprecedented fall in output and the long-term decline in investment after the global financial crisis. Through identification and evidence posted, we can safely say that the surge in FTS episodes over the last two decades is a crucial variable of significance in understanding business cycles. The explanatory power of FTS is promising and stands in contrast to the ineffectiveness of standard measures of productivity, sentiment, and expectations in explaining the slow recovery post-global financial crisis. This chapter has merely scratched the surface of the possible channels in which the Flight to Safety mechanism impacts both closed and open economies. There has been another surge in risk aversion during the Covid-19 phase, and therefore improved understanding of the Flight to Safety mechanism would be useful in making effective policies for recovery. In particular, what would be interesting to look out for in future research is an estimated micro-founded DSGE model with the causes and effects of the Flight to Safety phenomenon.

References

[1] Viral V. Acharya, Yakov Amihud, and Sreedhar T. Bharath. "Liquidity risk of corporate bond returns: conditional approach". In: *Journal of Financial Economics* 110.2 (2013), pp. 358–386.

[2] Viral V. Acharya and Lasse Heje Pedersen. "Asset pricing with liquidity risk". In: *Journal of Financial Economics* 77.2 (2005), pp. 375–410.

[3] Viral V. Acharya, Lasse Heje Pedersen, Thomas Philippon, and Matthew Richardson. "Measuring Systemic Risk". In: *The Review of Financial Studies* 30.1 (Oct. 2016), pp. 2–47.

[4] Tobias Adrian, Nina Boyarchenko, and Or Shachar. "Dealer balance sheets and bond liquidity provision". In: *Journal of Monetary Economics* 89 (2017). Carnegie-Rochester-NYU Conference Series on the Macroeconomics of Liquidity in Capital Markets and the Corporate Sector, pp. 92–109.

[5] Tobias Adrian and Hyun Song Shin. "Liquidity and leverage". In: *Journal of Financial Intermediation* 19.3 (2010). Risk Transfer Mechanisms and Financial Stability, pp. 418–437.

[6] Pooyan Amir Ahmadi and Harald Uhlig. *Sign Restrictions in Bayesian FaVARs with an Application to Monetary Policy Shocks*. NBER Working Papers 21738. National Bureau of Economic Research, Inc, Nov. 2015.

[7] Michelle Alexopoulos. “Read All about It!! What Happens Following a Technology Shock?” In: *American Economic Review* 101.4 (June 2011), pp. 1144–79.

[8] David Altig, Lawrence J. Christiano, Martin Eichenbaum, and Jesper Lindé. “Firm-specific capital, nominal rigidities and the business cycle”. In: *Review of Economic Dynamics* 14.2 (2011), pp. 225–247.

[9] Robert Amano and Malik Shukayev. “Risk Premium Shocks and the Zero Bound on Nominal Interest Rates”. In: *Journal of Money, Credit and Banking* 44.8 (Feb. 2012), pp. 1475–1505.

[10] Eurilton Araújo. “Investment-specific shocks and real business cycles in emerging economies: Evidence from Brazil”. In: *Economic Modelling* 29.3 (2012), pp. 671–678.

[11] Jonas E. Arias, Juan F. Rubio-Ramírez, and Daniel F. Waggoner. “Inference Based on Structural Vector Autoregressions Identified With Sign and Zero Restrictions: Theory and Applications”. In: *Econometrica* 86.2 (2018), pp. 685–720.

[12] Lieven Baele, Geert Bekaert, Koen Inghelbrecht, and Min Wei. *Flights to Safety*. Working Paper 19095. National Bureau of Economic Research, May 2013.

[13] Lieven Baele, Geert Bekaert, Koen Inghelbrecht, and Min Wei. “Flights to Safety”. In: *The Review of Financial Studies* 33.2 (June 2019), pp. 689–746.

[14] Scott R. Baker, Nicholas Bloom, and Steven J. Davis. “Measuring Economic Policy Uncertainty”. In: *The Quarterly Journal of Economics* 131.4 (July 2016), pp. 1593–1636.

[15] Ravi Bansal, Robert Dittmar, and Dana Kiku. “Cointegration and Consumption Risks in Asset Returns”. In: *The Review of Financial Studies* 22.3 (Nov. 2007), pp. 1343–1375.

[16] Ravi Bansal and Dana Kiku. “Cointegration and Long Run Asset Allocation”. In: *Journal of Business and Economic Statistics* 29.1 (Jan. 2011), pp. 161–173.

[17] Ravi Bansal and Amir Yaron. “Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles”. In: *The Journal of Finance* 59.4 (2004), pp. 1481–1509.

[18] Regis Barnichon. “Building a composite Help-Wanted Index”. In: *Economics Letters* 109.3 (2010), pp. 175–178.

[19] Robert J. Barro and Robert G. King. “Time-Separable Preferences and Intertemporal-Substitution Models of Business Cycles”. In: *The Quarterly Journal of Economics* 99.4 (Nov. 1984), pp. 817–839.

[20] Robert B. Barsky and Eric R. Sims. *News Shocks*. Working Paper 15312. National Bureau of Economic Research, Sept. 2009.

[21] Robert B. Barsky and Eric R. Sims. “News shocks and business cycles”. In: *Journal of Monetary Economics* 58.3 (Apr. 2011), pp. 273–289.

[22] Susanto Basu, John G. Fernald, Jonas D. M. Fisher, and Miles S. Kimball. *Sector-Specific Technical Change*. Mar. 2013.

[23] Susanto Basu, John G. Fernald, and Miles S. Kimball. “Are technology improvements contractionary?” In: *American Economic Review* 96.5 (Dec. 2006), pp. 1418–1448.

[24] Christiane Baumeister and Gert Peersman. “Time-Varying Effects of Oil Supply Shocks on the US Economy”. In: *American Economic Journal: Macroeconomics* 5.4 (Oct. 2013), pp. 1–28.

[25] Dirk G. Baur and Brian M. Lucey. “Flights and contagion—An empirical analysis of stock–bond correlations”. In: *Journal of Financial Stability* 5.4 (2009), pp. 339–352.

[26] Dirk G. Baur and Brian M. Lucey. “Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold”. In: *Financial Review* 45.2 (2010), pp. 217–229.

[27] Marianne Baxter and Robert G. King. “Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series”. In: *The Review of Economics and Statistics* 81.4 (1999), pp. 575–593.

[28] Paul Beaudry, Martial Dupaigne, and Franck Portier. “Modeling news-driven international business cycles”. In: *Review of Economic Dynamics* 14.1 (2011). Special issue: Sources of Business Cycles, pp. 72–91.

[29] Paul Beaudry and Bernd Lucke. “Letting Different Views about Business Cycles Compete”. In: *NBER Macroeconomics Annual* 24 (2010), pp. 413–456.

[30] Paul Beaudry, Deokwoo Nam, and Jian Wang. *Do Mood Swings Drive Business Cycles and is it Rational?* Working Paper 17651. National Bureau of Economic Research, Dec. 2011.

[31] Paul Beaudry and Franck Portier. "An exploration into Pigou's theory of cycles". In: *Journal of Monetary Economics* 51.6 (2004), pp. 1183–1216.

[32] Paul Beaudry and Franck Portier. *The News View of Economic Fluctuations: Evidence from Aggregate Japanese Data and Sectoral U.S. Data*. Working Paper 11496. National Bureau of Economic Research, Aug. 2005.

[33] Paul Beaudry and Franck Portier. "Stock Prices, News, and Economic Fluctuations". In: *American Economic Review* 96.4 (Sept. 2006), pp. 1293–1307.

[34] Paul Beaudry and Franck Portier. "News-Driven Business Cycles: Insights and Challenges". In: *Journal of Economic Literature* 52.4 (Dec. 2014), pp. 993–1074.

[35] Ben S. Bernanke, Mark Gertler, and Simon Gilchrist. "The Financial Accelerator and the Flight to Quality". In: *The Review of Economics and Statistics* 78.1 (1996), pp. 1–15.

[36] Ben S. Bernanke, Mark Gertler, and Simon Gilchrist. "Chapter 21 The financial accelerator in a quantitative business cycle framework". In: vol. 1. Handbook of Macroeconomics. Elsevier, 1999, pp. 1341–1393.

[37] Ben S. Bernanke and I. Mihov. "Measuring Monetary Policy". In: *The Quarterly Journal of Economics* 113.3 (Aug. 1998), pp. 869–902.

[38] Olivier Jean Blanchard and Danny Quah. "The Dynamic Effects of Aggregate Demand and Supply Disturbances". In: *American Economic Review* 79.4 (Sept. 1989), pp. 655–673.

[39] Nicholas Bloom. "The Impact of Uncertainty Shocks". In: *Econometrica* 77.3 (2009), pp. 623–685.

[40] Nicholas Bloom. "Fluctuations in uncertainty". In: *Journal of Economic Perspectives* 28.2 (2014), pp. 153–176.

[41] Christophe Boucher and Sessi Tokpavi. "Stocks and bonds: Flight-to-safety for ever?" In: *Journal of International Money and Finance* 95 (2019), pp. 27–43.

[42] Walter I. Boudry, Robert A. Connolly, and Eva Steiner. "What happens during flight to safety: Evidence from public and private real estate markets". In: *Real Estate Economics* (Nov. 2019), pp. 1–26.

[43] Chris Brooks. *Introductory Econometrics for Finance*. 4th ed. Cambridge University Press, 2019, pp. 293–333.

[44] Markus K. Brunnermeier and Stefan Nagel. "Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-evidence on Individuals". In: *American Economic Review* 98.3 (June 2008), pp. 713–36.

[45] Markus K. Brunnermeier and Lasse Heje Pedersen. "Market Liquidity and Funding Liquidity". In: *The Review of Financial Studies* 22.6 (Nov. 2008), pp. 2201–2238.

[46] Markus K. Brunnermeier and Yuliy Sannikov. "A Macroeconomic Model with a Financial Sector". In: *American Economic Review* 104.2 (Feb. 2014), pp. 379–421.

[47] Ricardo J. Caballero and Arvind Krishnamurthy. "Collective Risk Management in a Flight to Quality Episode". In: *The Journal of Finance* 63.5 (2008), pp. 2195–2230.

[48] Ricardo J. Caballero and Pablo Kurlat. "The 'Surprising' Origin and Nature of Financial Crises:A Macroeconomic Policy Proposal". In: *Proceedings - Economic Policy Symposium - Jackson Hole* (Sept. 2009), pp. 19–68.

[49] Dario Caldara, Cristina Fuentes-Albero, Simon Gilchrist, and Egon Zakrajšek. "The macroeconomic impact of financial and uncertainty shocks". In: *European Economic Review* 88 (Sept. 2016), pp. 185–207.

[50] John Y. Campbell and John H. Cochrane. "By Force of Habit: A Consumption Based Explanation of Aggregate Stock Market Behavior". In: *Journal of Political Economy* 107.2 (Apr. 1999), pp. 205–251.

[51] John Y. Campbell and Robert J. Shiller. "Yield Spreads and Interest Rate Movements: A Bird's Eye View". In: *The Review of Economic Studies* 58.3 (1991), pp. 495–514.

[52] Fabio Canova and Gianni De Nicoló. "Monetary disturbances matter for business fluctuations in the G-7". In: *Journal of Monetary Economics* 49.6 (Sept. 2002), pp. 1131–1159.

[53] Gilbert Cette, John G. Fernald, and Benoît Mojon. "The pre-Great Recession slowdown in productivity". In: *European Economic Review* 88.C (2016), pp. 3–20.

[54] V. V. Chari, Patrick J. Kehoe, and Ellen R. Mcgrattan. "Sticky price models of the business cycle: Can the contract multiplier solve the persistence problem?" In: *Econometrica* 68.5 (2000), pp. 1151–1179.

[55] Ian Christensen and Ali Dib. "The financial accelerator in an estimated New Keynesian model". In: *Review of Economic Dynamics* 11.1 (Jan. 2008), pp. 155–178.

[56] Lawrence J. Christiano, Martin Eichenbaum, and Robert Vigfusson. *What Happens After a Technology Shock?* NBER Working Papers 9819. National Bureau of Economic Research, Inc, 2003.

[57] Lawrence J. Christiano, Roberto Motto, and Massimo Rostagno. "Risk Shocks". In: *American Economic Review* 104.1 (Jan. 2014), pp. 27–65.

[58] John H. Cochrane. *Macro-Finance*. Working Paper 22485. National Bureau of Economic Research, Aug. 2016.

[59] John H. Cochrane. "Macro-Finance". In: *Review of Finance* 21.3 (Mar. 2017), pp. 945–985.

[60] Benjamin H Cohen, Peter Hördahl, and Dora Xia. "Term premia: models and some stylised facts". In: *BIS Quarterly Review* (Mar. 2018).

[61] Thomas F. Cooley and Edward C. Prescott. "Economic Growth and Business Cycles". In: *Frontiers of Business Cycle Research*. Princeton University Press, 1995, 1995. Chap. 1, pp. 1–38.

[62] John C. Cox, Jonathan E. Ingersoll, and Stephen A. Ross. "An Intertemporal General Equilibrium Model of Asset Prices". In: *Econometrica* 53.2 (1985), pp. 363–384.

[63] Richard K. Crump, Stefano Eusepi, and Emanuel Moench. *The term structure of expectations and bond yields*. Staff Reports 775. Federal Reserve Bank of New York, May 2016.

[64] Bianca De Paoli and Pawel Zabczyk. "Cyclical Risk Aversion, Precautionary Saving, and Monetary Policy". In: *Journal of Money, Credit and Banking* 45.1 (2013), pp. 1–36.

[65] Luca Dedola and Stefano Neri. “What Does a Technology Shock Do? A VAR Analysis with Model-based Sign Restrictions”. In: *Journal of Monetary Economics* 54 (Mar. 2007), pp. 512–549.

[66] Marco Del Negro, Frank Schorfheide, Frank Smets, and Rafael Wouters. “On the Fit of New Keynesian Models”. In: *Journal of Business and Economic Statistics* 25.2 (2007), pp. 123–143.

[67] Francis X. Diebold, Monika Piazzesi, and Glenn D. Rudebusch. “Modeling Bond Yields in Finance and Macroeconomics”. In: *American Economic Review* 95.2 (May 2005), pp. 415–420.

[68] John Donaldson and Rajnish Mehra. *Risk Based Explanations of the Equity Premium*. NBER Working Papers 13220. National Bureau of Economic Research, Inc, 2007.

[69] Eugene F. Fama and Robert R. Bliss. “The Information in Long-Maturity Forward Rates”. In: *The American Economic Review* 77.4 (1987), pp. 680–692.

[70] Jon Faust. “The robustness of identified VAR conclusions about money”. In: *Carnegie-Rochester Conference Series on Public Policy* 49 (Dec. 1998), pp. 207–244.

[71] John G. Fernald. *A Quarterly, Utilisation-Adjusted Series on Total Factor Productivity*. Working Paper Series 2012-19. Federal Reserve Bank of San Francisco, Apr. 2012. eprint: https://www.frbsf.org/economic-research/publications/working-papers/2012/19/.

[72] Jesús Fernández-Villaverde, Pablo A Guerrón-Quintana, Juan F. Rubio-Ramírez, and Martín Uribe. *Risk Matters: The Real Effects of Volatility Shocks*. Working Paper 14875. National Bureau of Economic Research, Apr. 2009.

[73] Jonas D. M. Fisher. “The Dynamic Effects of Neutral and Investment-Specific Technology Shocks”. In: *Journal of Political Economy* 114.3 (2006), pp. 413–451.

[74] Neville Francis and Valerie A. Ramey. “Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited”. In: *Journal of Monetary Economics* 52.8 (Nov. 2005), pp. 1379–1399.

[75] Neville Francis and Valerie A. Ramey. “The Source of Historical Economic Fluctuations: An Analysis Using Long-Run Restrictions”. In: *NBER International Seminar on Macroeconomics 2004*. NBER Chapters. National Bureau of Economic Research, Inc, 2006, pp. 17–73.

[76] Francesco Furlanetto and Martin Seneca. “Investment shocks and consumption”. In: *European Economic Review* 66 (2014), pp. 111–126.

[77] Jordi Galí. “Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations?” In: *American Economic Review* 89.1 (1999), pp. 249–271.

[78] Jordi Galí. *Monetary policy, inflation, and the business cycle : an introduction to the new Keynesian framework and its applications*. Princeton University Press, 2015, p. 279.

[79] Luca Gambetti and Alberto Musso. *The macroeconomic impact of the ECB's expanded asset purchase programme (APP)*. Working Paper Series 2075. European Central Bank, June 2017.

[80] Gita Gopinath, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez. “Capital Allocation and Productivity in South Europe”. In: *The Quarterly Journal of Economics* 132.4 (June 2017), pp. 1915–1967.

[81] Jeremy Greenwood, Zvi Hercowitz, and Per Krusell. “Long-Run Implications of Investment-Specific Technological Change”. In: *The American Economic Review* 87.3 (1997), pp. 342–362.

[82] Jeremy Greenwood, Zvi Hercowitz, and Per Krusell. “The role of investment-specific technological change in the business cycle”. In: *European Economic Review* 44.1 (Jan. 2000), pp. 91–115.

[83] Robin Greenwood, Samuel G. Hanson, and Jeremy C. Stein. “A Comparative-Advantage Approach to Government Debt Maturity”. In: *The Journal of Finance* 70.4 (2015), pp. 1683–1722.

[84] Veronica Guerrieri and Robert Shimer. “Dynamic Adverse Selection: A Theory of Illiquidity, Fire Sales, and Flight to Quality”. In: *American Economic Review* 104.7 (July 2014), pp. 1875–1908.

[85] Lars Peter Hansen, Thomas J. Sargent, and Thomas D. Tallarini. “Robust Permanent Income and Pricing”. In: *The Review of Economic Studies* 66.4 (Oct. 1999), pp. 873–907.

[86] Zhiguo He and Arvind Krishnamurthy. “Intermediary Asset Pricing”. In: *American Economic Review* 103.2 (Apr. 2013), pp. 732–70.

[87] Nikolay Hristov, Oliver Hülsewig, and Timo Wollmershäuser. "Loan supply shocks during the financial crisis: Evidence for the Euro area". In: *Journal of International Money and Finance* 31.3 (2012). Financial Stress in the Eurozone, pp. 569–592.

[88] Nir Jaimovich and Sergio T. Rebelo. "Can News about the Future Drive the Business Cycle?" In: *American Economic Review* 99.4 (Sept. 2009), pp. 1097–1118.

[89] Urban J. Jermann and Vincenzo Quadrini. "Macroeconomic Effects of Financial Shocks". In: *American Economic Review* 102.1 (Feb. 2012), pp. 238–71.

[90] Alejandro Justiniano, Giorgio E. Primiceri, and Andrea Tambalotti. "Investment shocks and business cycles". In: *Journal of Monetary Economics* 57.2 (2010), pp. 132–145.

[91] Alejandro Justiniano, Giorgio E. Primiceri, and Andrea Tambalotti. "Investment shocks and the relative price of investment". In: *Review of Economic Dynamics* 14.1 (2011). Special issue: Sources of Business Cycles, pp. 102–121.

[92] Günes Kamber, Christie Smith, and Christoph Thoenissen. "Financial frictions and the role of investment-specific technology shocks in the business cycle". In: *Economic Modelling* 51.C (Dec. 2015), pp. 571–582.

[93] John Maynard Keynes. *The general theory of employment, interest and money*. Macmillan, London, 1936.

[94] Hashmat Khan and John Tsoukalas. "Investment shocks and the comovement problem". In: *Journal of Economic Dynamics and Control* 35.1 (2011), pp. 115–130.

[95] Lutz Kilian. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market". In: *American Economic Review* 99.3 (June 2009), pp. 1053–69.

[96] Lutz Kilian and Daniel P. Murphy. "Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market VAR models". In: *Journal of the European Economic Association* 10.5 (2012), pp. 1166–1188.

[97] Don H. Kim and Jonathan H. Wright. *An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates*. Finance and Economics Discussion Series 2005-33. Board of Governors of the Federal Reserve System (U.S.), 2005.

[98] Robert G. King and Sergio T. Rebelo. "Resuscitating real business cycles". In: *Handbook of Macroeconomics*. Ed. by J. B. Taylor & M. Woodford. Vol. 1. PART B. Elsevier, Jan. 1999, pp. 927–1007.

[99] Nobuhiro Kiyotaki and John Moore. "Credit Cycles". In: *Journal of Political Economy* 105.2 (1997), pp. 211–248.

[100] Martin Kliem and Alexander Meyer-Gohde. *(Un)expected monetary policy shocks and term premia*. eng. Bundesbank Discussion Paper 30/2017. 2017.

[101] Emanuel Kopp and Peter D. Williams. "A Macroeconomic Approach to the Term Premium". In: *Econometrics: Multiple Equation Models eJournal* (2018).

[102] Manfred Kremer, Marco Lo Duca, and Dániel Holló. *CISS - a composite indicator of systemic stress in the financial system*. Working Paper Series 1426. European Central Bank, Mar. 2012.

[103] Finn E. Kydland and Edward C. Prescott. "Time to Build and Aggregate Fluctuations". In: *Econometrica* 50.6 (1982), pp. 1345–1370.

[104] Sang-Sub Lee. "Macroeconomic Sources of Time-Varying Risk Premia in the Term Structure of Interest Rates". In: *Journal of Money, Credit and Banking* 27.2 (1995), pp. 549–569.

[105] Helmut Luetkepohl. *Vector Autoregressive Models*. Economics Working Papers ECO2011/30. European University Institute, 2011.

[106] Alfred Marshall. *Principles of Economics*. 1890.

[107] Rajnish Mehra. "The Equity Premium: Why is it a Puzzle?" In: *Financial Analysts Journal* 59 (Mar. 2003).

[108] Rajnish Mehra and Edward C. Prescott. "The equity premium: A puzzle". In: *Journal of Monetary Economics* 15.2 (1985), pp. 145–161.

[109] Rossana Merola. "The role of financial frictions during the crisis: An estimated DSGE model". In: *Economic Modelling* 48 (Aug. 2015). Special Issue on Current Challenges on Macroeconomic Analysis and International Finance Modelling, pp. 70–82.

[110] Dale T. Mortensen and Christopher A. Pissarides. "Job Creation and Job Destruction in the Theory of Unemployment". In: *The Review of Economic Studies* 61.3 (1994), pp. 397–415.

[111] Andrew Mountford and Harald Uhlig. “What are the effects of fiscal policy shocks?” In: *Journal of Applied Econometrics* 24.6 (2009), pp. 960–992.

[112] Emi Nakamura, Dmitriy Sergeyev, and Jón Steinsson. “Growth-Rate and Uncertainty Shocks in Consumption: Cross-Country Evidence”. In: *American Economic Journal: Macroeconomics* 9.1 (Jan. 2017), pp. 1–39.

[113] Deokwoo Nam and Jian Wang. “Mood Swings and Business Cycles: Evidence from Sign Restrictions”. In: *Journal of Money, Credit and Banking* 51.6 (2019), pp. 1623–1649.

[114] Charles Nolan and Christoph Thoenissen. “Financial shocks and the US business cycle”. In: *Journal of Monetary Economics* 56.4 (May 2009), pp. 596–604.

[115] Vasia Panousi and Dimitris Papanikolaou. *Investment, idiosyncratic risk, and ownership*. Finance and Economics Discussion Series 2011-54. Board of Governors of the Federal Reserve System (U.S.), 2011.

[116] Gert Peersman and Roland Straub. “Technology shocks and robust sign restrictions in a Euro area SVAR”. In: *International Economic Review* 50.3 (2009), pp. 727–750.

[117] Valerie A. Ramey. “Macroeconomic Shocks and Their Propagation”. In: vol. 2. Elsevier B.V., Jan. 2016, pp. 71–162.

[118] Sergio T. Rebelo. “Real Business Cycle Models: Past, Present and Future”. In: *The Scandinavian Journal of Economics* 107.2 (2005), pp. 217–238.

[119] Paul M. Romer. “Endogenous Technological Change”. In: *Journal of Political Economy* 98.5 (Oct. 1990), S71–S102.

[120] Robert J. Shiller. *Irrational Exuberance*. 3rd ed. Princeton University Press, 2015.

[121] Robert Shimer. “The Cyclical Behavior of Equilibrium Unemployment and Vacancies”. In: *American Economic Review* 95.1 (May 2005), pp. 25–49.

[122] Christopher A. Sims. “Comparison of Interwar and Postwar Business Cycles: Monetarism Reconsidered”. In: *The American Economic Review* 70.2 (1980), pp. 250–257.

[123] Christopher A. Sims. “Macroeconomics and Reality”. In: *Econometrica* 48.1 (1980), pp. 1–48.

[124] Christopher A. Sims. “Are forecasting models usable for policy analysis?” In: *Quarterly Review* 10.Win (1986), pp. 2–16.

[125] Frank Smets and Rafael Wouters. “Shocks and frictions in US business cycles: A Bayesian DSGE approach”. In: *American Economic Review* 97.3 (June 2007), pp. 586–606.

[126] Luke Stein and Elizabeth Stone. “The Effect of Uncertainty on Investment, Hiring, and R&D: Causal Evidence from Equity Options”. In: *SSRN Electronic Journal* (July 2010).

[127] James Stock, Christopher A. Sims, and Mark W. Watson. “Inference in Linear Time Series Models with Some Unit Roots”. In: *Econometrica* 58.1 (1990), pp. 113–144.

[128] James H. Stock and Mark W. Watson. “Business Cycle Fluctuations in U.S. Macroeconomic Time Series”. In: ed. by J. Taylor and M. Woodford. Amsterdam: Elsevier, 1999, pp. 3–64.

[129] James H. Stock and Mark W. Watson. “Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics”. In: vol. 2. Elsevier B.V., 2016, pp. 415–525.

[130] Konstantinos Theodoridis and Haroon Mumtaz. *Dynamic Effects of Monetary Policy Shocks on Macroeconomic Volatility*. Working Papers 101219932. Lancaster University Management School, Economics Department, 2015.

[131] Robert M. Townsend. “Optimal contracts and competitive markets with costly state verification”. In: *Journal of Economic Theory* 21.2 (Oct. 1979), pp. 265–293.

[132] Harald Uhlig. “What are the effects of monetary policy on output? Results from an agnostic identification procedure”. In: *Journal of Monetary Economics* 52.2 (2005), pp. 381–419.

[133] Dimitri Vayanos. *Flight to Quality, Flight to Liquidity, and the Pricing of Risk*. Working Paper 10327. National Bureau of Economic Research, Feb. 2004.

A Numerical approach to sign restrictions

Uhlig (2005) shows that $a \in \mathbb{R}^m$ is an impulse vector iff a is a column of $\boldsymbol{A}$ such that $\boldsymbol{A}$ is a decomposition of the variance-covariance matrix $\Sigma = \boldsymbol{A}\boldsymbol{A}'$ (see Equ. 6). Let $\tilde{A}\tilde{A}'$ be a Cholesky decomposition of Σ, then a is an impulse vector iff

$$a = \tilde{A}\alpha \tag{22}$$

for some vector α of unit length. Let $r_i(k) \in \mathbb{R}^m$ be the vector response at k horizon to ith shock in Cholesky decomposition of Σ. Then the impulse response to a is given by

$$r_a(k) = \sum_{i=1}^{m} \alpha_i r_i(k) \tag{23}$$

Given some $\boldsymbol{B} = [\boldsymbol{B'_{(1)}}, ..., \boldsymbol{B'_{(l)}}]$, variance-covariance matrix Σ and some K period ahead forecast horizon after the shock, we need to obtain $\mathcal{A}(\boldsymbol{B}, \Sigma, K)$ the set of all such impulse vectors. One approach is to use the OLS estimate of VAR, $B = \hat{B}$ and $\Sigma = \hat{\Sigma}$, for a few choices of K. Monte-Carlo methods can be applied to pick impulse vectors that lie in set $\mathcal{A}$ and obey the sign restrictions. The maximum and minimum of those impulse responses can be plot to get an estimate of the bounds of the impulse responses. Analytically Uhlig (2005) discusses a way of making inference on these impulse responses, by making the following assumption.

Assumption A.1. Let $\tilde{A}(\Sigma)$ be the lower-triangular Cholesky factorisation of Σ. Let $\mathcal{P}_m$ be the space of positive-definite $m \times m$ matrices and $\mathcal{S}_m$ be the unit sphere in $\mathbb{R}^m$, $\mathcal{S}_m = \{\alpha \in \mathbb{R}^m : ||\alpha|| = 1\}$. The parameters $(\boldsymbol{B}, \Sigma, \alpha)$ are jointly drawn from a prior on $\mathbb{R}^{l\times m\times m} \times \mathcal{P}_m \times \mathcal{S}_m$. For both criteria function and sign-restrictions approach, this prior is proportional to a Normal-Wishart prior in $(\boldsymbol{B}, \Sigma)$ whenever the impulse vector $a = \tilde{A}(\Sigma)\alpha$ satisfies $a \in \mathcal{A}(\boldsymbol{B}, \Sigma, K)$ and zero elsewhere.

If we make this assumption, the impulse vector is parameterized in $\mathcal{A}(\boldsymbol{B}, \Sigma, \alpha)$ space rather than $\mathcal{A}(\boldsymbol{B}, \Sigma, a)$ space. So the prior is proportional to the Normal-Wishart prior times an indicator function on $\tilde{A}(\Sigma)\alpha \in \mathcal{A}(\boldsymbol{B}, \Sigma, K)$. Therefore, the posterior is given by usual posterior on $(\boldsymbol{B}, \Sigma)$ times the indicator function $\tilde{A}(\Sigma)\alpha \in \mathcal{A}(\boldsymbol{B}, \Sigma, K)$.

To draw inference (in the sign-restrictions approach) from this posterior, jointly draw from unrestricted Normal-Wishart posterior for $(\boldsymbol{B}, \Sigma)$ as well as a uniform distribution over the unit sphere $\alpha \in \mathcal{S}_m$. Construct impulse vector using (22) and calculate impulse responses $r_a(k, j)$ for $k = 1, 2...K$ horizons, for the j variables (which are restricted in sign for the K horizon periods). If all the impulse responses obey sign restrictions, keep the draw, otherwise discard it. Repeat sufficiently (for 200 times) and do inference on the draws kept.

In the criteria function approach, a penalty function $f(j)$ is written which penalises the impulse response of a variable in the expected direction (positive or negative after the shock) significantly less than what it penalises the response in the opposite of expected direction. The impulse vector a is then defined as the vector that minimises the total penalty function $\psi(a)$ which is the sum of all impulse responses for all variables (of interest) to the shock. Calculating the impulse response in this way requires numerical minimisation. Save both the draw which is made from the Normal-Wishart prior on $(\boldsymbol{B}, \Sigma)$ and the resulting impulse vector for statistical analysis. In order to obtain inference in this approach, make Assumption A.1 and use Monte-Carlo method to pick $n = 100$ draws from it. Do numerical minimisation of the total penalty function $\psi(a)$ on each draw and save the results.

B High-frequency approach to FTS

The structural VAR analysis of the FTS shocks on the macroeconomy has identified the FTS shocks for the benchmark model with respect to identification strategy 1. In this section, I discuss another method from the literature that has been considered in generating FTS series. This comparative analysis follows from Baele, Bekaert, Inghelbrecht, and Wei (2013) in defining FTS as days of high stress and high volatility in asset markets that coincide with days of negative stock-bond return correlation where equity returns are negative and bond returns are positive. Baele, Bekaert, Inghelbrecht, and Wei (2013) used a plethora of econometric techniques to develop specific measures of FTS. Based on daily returns data of benchmark equity index (risky asset) and benchmark 10-yr treasury bond (safe and liquid asset) they have found that on average FTS days are less than 3% of the sample (trading days between 1980 to 2013 of 23 developed countries), and that bond returns exceed equity returns by 2.5 to 4% on FTS days.

One of their techniques is to develop a continuous signal between interval $[0, 1]$ that signifies the probability or likelihood of FTS occurring on that day. This measure identifies FTS as a day of occurrence of extremely negative stock return and simultaneously an extremely positive bond return. Therefore, for country i FTS is given by

$$FTS_{i,t} = \mathbb{1}\{r^b_{i,t} > z_{i,b}\} \text{ x } \mathbb{1}\{r^s_{i,t} > z_{i,s}\} \tag{24}$$

where $\mathbb{1}$ is the indicator function, $r^b_{i,t}, r^s_{i,t}$ are country specific return on bond and stocks index, and $z_{i,b}, z_{i,s}$ are time-varying country specific thresholds that are directly related to time varying volatility of bond/equity returns. The key variable in derivation of the FTS days then is the time-varying threshold parameters, z_b, z_s that is k standard deviations from time-varying volatilites $\sigma_{b,t}$, $\sigma_{s,t}$.

$$z_b = k\sigma_{b,t} \quad \text{and} \quad z_s = k\sigma_{s,t} \tag{25}$$

There are a couple of methods that can be used to generate this time-varying volatility of stock and bond prices. A common approach is to fit a Garch (1,1) on the daily return series. This approach is based on using the Gaussian kernel, which treats both past and future observations as equally significant in generating the volatility of any given date. This paper instead relies on Baele, Bekaert, Inghelbrecht, and Wei (2019) approach that identifies the time-varying long and short-run volatility by employing backwards-looking Gaussian kernel density estimator[14]. For long-run volatility estimation, a normal density kernel is used over past 255 (i.e. near 1 year of trading days), and the weights on the previous 5 days are ignored. The short-run volatility is estimated by using the backwards-looking kernel over the last 5 days (i.e. 1 week of trading days). The volatility is modelled using a simple kernel method is discussed in the next subsection.

B.1 Kernel density based conditional volatility

Kernel methodology from Baele, Bekaert, Inghelbrecht, and Wei (2019) for finding the short and long run variances and covariances is reproduced for the avid reader. Given any date t_0 in a sample $t = 1, ..., T$. The kernel method calculates the variances of returns $r_{i,t}$ at a normalised date, $\tau = t_0/T \in [0, 1]$ as

$$\sigma^2_{i,\tau} = \sum_{t=1}^{T} K_h(t/T - \tau) r^2_{i,t} \qquad i = s, b \tag{26}$$

where the weights $K_h(z) = K(z/h)/h$ are dependent on how close the observations are to the point of interest τ, the size of chosen bandwidth $h > 0$, and the specific

[14] Page 5 of Baele, Bekaert, Inghelbrecht and Wei (2013)

functional form of kernel density estimator. Baele, Bekaert, Inghelbrecht, and Wei (2019) suggest the following backward looking Gaussian Kernel.

$$K(z) = \frac{\psi}{2} exp\left(\frac{z^2}{2}\right) \quad \text{if} \quad z \leq \frac{t-l}{T} \tag{27}$$

$$K(z) = 0 \quad \text{if} \quad z > \frac{t-l}{T} \tag{28}$$

The scaling factor ψ is used to make the weights sum to 100% and l is the number of past days that are ignored in the variance calculation. For long-run variances, a bandwidth h of 255 days is chosen, and the last 5 observations ($l = 5$) are ignored. In short-run variances the size of h is 5 days and no observations are ignored, ($l = 0$). The time-varying short and long-run covariance between equity and bond return is calculated using the same Kernel density estimator to the cross-product of bond and equity returns. The time-varying correlation between these assets is then given by the ratio of the stock-bond covariance to the product of stock and bond volatilities. Once the time-varying volatilities and covariances are determined, we proceed in the next section to generate an FTS incidence indicator by using either a Threshold-based or an Ordinal rank-based approach. Figure 7 on page 21 highlights the results from short and long-run variance and covariance produced from the backwards-looking Kernel methods. A comparison between this nuanced backwards-looking Kernel-based method and a trivial alternative Rolling days method is made in Figure 23 on page 123. The rolling days method chooses past 250 days of returns for calculating long run time-varying volatility and chooses past 5 days of returns for calculating the short run time-varying volatility. The rolling days method places equal weights to all past observations and therefore has higher peaks and lower troughs.

B.2 Threshold approach to FTS

The first approach to identify FTS days is based on the coexeedance approach in Baele, Bekaert, Inghelbrecht, and Wei (2013) that studies contagion across emerging markets by counting joint occurrences of extreme (or beyond a certain threshold) events. The significance of the events is compared to what would be expected under certain normal distributions.

Denote $r_t = (r_{e,t}, -r_{b,t})$ as the series of observed equity returns and negative of observed bond returns. The change of sign of the bond return observation is crucial. Recall that the FTS event is marked by a joint observation of bond returns being above a defined positive threshold and equity returns being below a defined negative threshold. If such a cumulative density function under the assumption of joint normality between stock and negative of bond returns were to be plotted on a two-dimensional grid with equity returns on the horizontal axis and the negative of bond returns on the vertical axis. It would showcase an FTS event to be lying in the bottom left, or south-west corner also known as the third quadrant of the two-axis coordinate system. Assuming that both equity and bond returns are normally distributed, with mean zero, so $r_{i,t} \sim N(0, \Omega_t)$. In this joint normal distribution the cumulative probability of a threshold that is set equal to negative (κ) times the standard deviation of the respective equity and bond returns is given as,

$$Prob_{ths,t} = N_{cdf}\left(\begin{bmatrix} -\kappa\sigma_{e,t} \\ -\kappa\sigma_{b,t} \end{bmatrix}, 0, \Omega_t\right) \tag{29}$$

where the variance-covariance matrix Ω_t consists of the variances of bond and equity return, $\sigma_{e,t}$ and $\sigma_{b,t}$ are respective time-varying volatilities, and the covariance between equity and negative of bond returns $\rho_{(e,-b),t}$ is,

$$\Omega_t = \begin{bmatrix} \sigma^2_{e,t} & \rho_{(e,-b),t} \\ \rho_{(e,-b),t} & \sigma^2_{b,t} \end{bmatrix} \tag{30}$$

The threshold κ can be calibrated to deliver on a targeted number of events that are considered extreme or demonstrate FTS. An observation is considered extreme (or demonstrates FTS) when the $Prob_{obs,t}$ is less than $Prob_{ths,t}$, i.e. the observed equity returns and negative of bond returns are below the threshold,

$$Prob_{obs,t} < Prob_{ths,t} = Prob\begin{bmatrix} r_{e,t} < -\kappa\sigma_{e,t} \\ -r_{b,t} < -\kappa\sigma_{b,t} \end{bmatrix} \tag{31}$$

Therefore the probability of FTS in the threshold method can be calculated as

$$FTS_t = \mathbb{1}\{r_{b,t} > 0\} \text{ x } \mathbb{1}\{r_{s,t} < 0\} \text{ x } \mathbb{1}\{Prob_{obs,t} < Prob_{ths,t}\} \text{ x } (1 - Prob_{obs,t}) \tag{32}$$

where the first term checks if the bond returns are positive, the second term checks if the stock return is negative and the third indicator function marks extreme events, i.e. when the cumulative probability of the event is lower than the cumulative probability of the threshold event. Once a day is deemed to have exhibit FTS, the last term puts a higher probability to more extreme events. So for a threshold probability of 0.04, only an observation that has strictly negative stock return, strictly positive bond return and has a cumulative probability density of $Prob_{obs} < 0.04$ can be counted as an FTS event. The FTS probability of that date is then set to be $1 - Prob_{obs}$, which will be greater than 0.96.

Whether an event would be extreme enough to be characterised as an FTS depends on the threshold κ, for instance, if we choose the threshold κ to be equal to 1.25 (time-varying) standard deviation below the mean equity or negative bond return, this would lead to a higher number of FTS days than we would get by setting a threshold κ of 2.0. Figure 24 on page 124 plots the FTS incidence, calculated using the Threshold method, for different choices of the threshold (κ). In fig. 24, the threshold probability is time-varying as it depends on the time-varying volatilities of stock and bond returns.

B.3 Ordinal index approach to FTS

Another way to identify FTS using kernel density based measure of time-varying volatility of returns and a threshold criteria, is the Ordinal index approach. This alternative method is based on Kremer, Lo Duca, and Holló (2012) composite measure of determining stress in financial system. Their method generates the composite index by aggregating the empirical (ranked) cumulative probability distribution over several indicators. So far, we have used the definition of FTS as the extreme chance of generating excess positive bond returns and excess negative equity returns. To this, using Baele, Bekaert, Inghelbrecht, and Wei (2019), we can add several other features of the market that accompany any FTS event, such as:
Strong features:
a) the size of difference between bond and equity return,
b) the dip in the difference between long and short run stock-bond correlation,
c) the spike in the difference between short term and long term equity return volatility.
and Weak features:
d) strictly negative bond return and strictly positive equity return,
e) short-term bond equity return correlation is negative and strictly below the long-term level,
f) ratio of short term to long term equity volatility is above a threshold k such that $k > 1$.

Once we have the time-varying long and short term volatility, the value of these six features for any day in the sample can be easily calculated using daily stock and bond market returns. The three strong features are all continuous data and are structured so that a high values occurs on days of FTS. The three weak features are binary, indicating whether the feature is achieved or not on any day in the sample, these are expected to take their 'true' value for FTS days. A combination of these results can be used to develop a continuous series of FTS likelihood for any day in the sample.

The procedure begins by generating ordinal ranks for each observation on each of the three strong features in the entire sample. The ordinal rankings for each feature are normalised to be $\in [0, 1]$. Thereafter a composite rank $\in [0, 1]$ for each day in the sample is obtained by averaging its ranking on the three strong features. Therefore an ordinal incidence rank of 0.9 or of 90% for a day in our sample signifies that only 10% of the total days in the sample have higher average ordinal rank than that particular day. This ordinal number can be read as a FTS likelihood series, where the closer the averaged rank gets to 1, the higher is the likelihood of FTS event occurring on that day. This estimate of the FTS likelihood can be futher improved by considering the weak features of FTS days.

Consider the Ordinal rank of all days that satisfy the weak symptoms of FTS, and consider the lowest of these ranks as a threshold. All days in the sample with ordinal rank below the rank of threshold are allocated an FTS probability of zero. The FTS probability of the threshold is assigned as 1 minus the probability of its 'false positives'. In order to obtain the 'false positives' for the threshold number, first determine the number of days in the sample that have an ordinal rank larger than the rank of the threshold, and then calculate the percentage of those days that fail to satisfy all of the three weak symptoms of FTS. Similarly we could rely on the weak features to obtain FTS probability measure for the observations that have an ordinal rank above the ordinal rank of threshold. FTS Probability of those observations is also equal to one minus the probability of observing their 'false positives'.

For instance, suppose that the ordinal rank on 3rd Aug 2018 is 0.7 which is greater than the ordinal rank of threshold 0.62 for that day. And of the 300 days in the sample that have an ordinal rank above 0.7, near 23% fail to satisfy all three weak features of FTS, then the 'false positive' probability of 3rd Aug 2018 is 23% and its FTS probability is given by $(1 - 23\%) = 67\%$.

The choice of threshold in this setup is determined by the lowest ordinal rank that satisfies the 3 weak features, however the third of those weak features involves subjectivity in the choice of $k > 1$, i.e. the ratio of short to long term equity volatility should be above k on FTS days, where k could be any number greater than 1 that could be chosen by the researcher. Based on different choices of k, Figure 25 on page 125 plots the FTS incidences and their probabilities.

B.4 FTS and FTR days

The results of the threshold approach are presented for various levels of threshold κ in fig. 24, and the results from the ordinal approach are presented in fig. 25. In both these approaches as we increase the threshold criteria (κ or $Prob_{ths}$ or k), there is a decrease in FTS days. Therefore to obtain the desired level of FTS likelihood, a relevant threshold can be calibrated.

The daily FTS series is aggregated to generate a monthly and quarterly series. The charts in Figure 27 describe this aggregation for the Ordinal index approach for $k = 1.25$. While it is straightforward to interpret the frequency charts in fig. 27, as the total number of FTS events that occurred in a given time frame, interpreting the quarterly aggregate of FTS probability as given in fig. 27 can be a bit confusing, but it is relevant to get the full incidence and impact of FTS events that may be missing from an aggregated series that is only based on frequency. In a frequency-based aggregation, a quarter with 4 FTS events is weighted higher than a quarter with 3 FTS events. However, it is possible that the 3 FTS events were all very extreme occurrences while the 4 FTS events were mild. Therefore an aggregate measure that sums up the extremity of FTS events is required. One approach to achieve this is by aggregating the sums of FTS probability in each quarter and dividing it by 62.5, which is the number of trading days in a quarter. This gives us a measure of the likelihood or probability of FTS days in that quarter.

Based on this aggregation we witness from both the heatmaps (in fig. 6 on page 19 and the bubbles chart in fig. 27 on page 127) that there is a higher likelihood of FTS cases in periods surrounding the events of global market distress, such as the inflation of 70s, the Russia, Tequilla and Asian crisis, the Dot-com bubble and the Great Recession. There is also an upsurge in FTS events and probability in the last 5 years.

Similarly, we can run a complimentary exercise using the same methods, i.e. the ordinal index and the threshold approach to generate a Flight to Risk (FTR) variable. This can be achieved by considering periods when the return on equity index is positive and return on the bond index is negative, and this difference is above a threshold when using the threshold method, or if using the Ordinal method, the ordinal ranking of such days lies is in tails of a fitted cumulative probability distribution. A comparison of FTS and FTR days using the ordinal index method with threshold k of 1, as shown in Figure 26 on page 126, demonstrates that incidence of both FTS and FTR events has increased since the late 1990s and that FTS events have bigger and more frequent spikes than FTR.

C Tables

Table 6: FEVD of Investment with Identification Strategy 1

Horizon	TFP	FTS	MP	SRatio	Residual
1	12.97	17.51	13.08	7.67	9.26
	(1.46, 44.78)	(2.47, 49.93)	(1.45, 45.92)	(0.89, 32.67)	(0.81, 40.68)
4	9.39	38.13	9.62	11.46	8.00
	(1.77, 34.73)	(8.38, 64.47)	(1.89, 26.36)	(1.73, 35.46)	(2.00, 30.86)
8	7.54	37.35	8.69	13.96	8.92
	(1.22, 30.02)	(6.29, 64.09)	(1.75, 22.89)	(2.35, 38.12)	(2.16, 30.59)
12	7.75	40.45	8.39	11.80	8.21
	(1.69, 31.57)	(8.90, 66.37)	(1.61, 20.80)	(2.15, 35.60)	(2.02, 28.34)
16	8.64	42.46	7.76	11.15	7.93
	(2.15, 32.39)	(10.77, 66.06)	(1.94, 20.29)	(2.17, 34.50)	(1.95, 26.81)
20	9.25	42.77	7.63	10.97	7.77
	(2.69, 33.52)	(11.45, 65.29)	(2.16, 20.13)	(2.44, 34.26)	(2.27, 26.13)
24	9.82	42.53	7.71	11.00	7.91
	(2.93, 33.87)	(11.86, 64.32)	(2.49, 20.16)	(2.60, 33.54)	(2.34, 25.81)
28	10.17	42.17	8.04	11.03	8.01
	(3.17, 33.64)	(12.16, 63.72)	(2.75, 20.16)	(2.80, 32.99)	(2.47, 25.58)
30	10.22	41.99	8.16	11.05	8.11
	(3.37, 33.64)	(12.27, 63.50)	(2.94, 20.21)	(2.82, 32.74)	(2.48, 25.50)

Notes: FEVD of Private Investment from all shocks in the benchmark model identified with Identification Strategy 1. Median level and 68% confidence bands are reported.

Table 7: FEVD of Investment in Great Moderation period

Horizon	TFP	FTS	MP	SRatio	Residual
1	10.56	10.62	19.96	11.90	11.44
	(0.72, 42.80)	(1.24, 30.78)	(3.09, 66.15)	(0.65, 38.26)	(0.70, 41.78)
4	9.18	20.23	14.90	13.40	12.41
	(2.05, 34.70)	(5.44, 48.47)	(3.43, 41.11)	(2.56, 44.71)	(1.94, 34.98)
8	7.86	24.51	14.38	12.04	10.33
	(1.29, 35.73)	(5.46, 57.31)	(3.15, 37.26)	(1.92, 42.57)	(1.23, 32.53)
12	7.84	24.18	14.51	11.84	10.62
	(1.09, 35.76)	(5.14, 56.29)	(3.30, 38.31)	(1.82, 42.67)	(1.47, 32.39)
16	8.27	24.18	15.97	12.27	10.73
	(1.51, 35.47)	(4.78, 54.72)	(3.85, 38.15)	(2.13, 41.80)	(1.86, 33.13)
20	8.62	23.51	16.84	12.14	10.67
	(2.20, 36.61)	(4.57, 53.21)	(4.65, 39.58)	(2.94, 40.57)	(2.55, 31.64)
24	9.62	22.70	17.59	12.77	10.81
	(3.08, 35.45)	(4.60, 51.32)	(5.60, 39.82)	(3.57, 39.84)	(3.34, 31.11)
28	10.63	21.70	17.62	12.52	11.84
	(3.84, 34.26)	(4.53, 49.54)	(6.58, 39.68)	(3.97, 39.09)	(4.08, 31.35)
30	10.97	21.37	17.74	12.77	11.81
	(4.11, 33.72)	(4.53, 48.56)	(6.84, 39.41)	(4.18, 39.17)	(4.44, 31.55)

Notes: FEVD of Private Investment from all shocks in the benchmark model in Great Moderation period data (1983-2007) identified with Identification Strategy 1. Median level and 68% confidence bands are reported.

Table 8: FEVD of Investment in Pre-Great Moderation period

Horizon	TFP	FTS	MP	SRatio	Residual
1	8.78	7.45	14.98	23.12	16.82
	(2.14, 23.52)	(0.61, 25.97)	(1.02, 48.08)	(2.73, 57.36)	(1.22, 47.26)
4	5.50	9.67	8.56	32.62	21.52
	(3.11, 15.10)	(1.82, 34.20)	(1.47, 29.15)	(5.28, 57.94)	(4.79, 56.39)
8	18.76	6.32	5.86	29.73	25.60
	(12.32, 27.66)	(1.32, 21.99)	(2.35, 23.02)	(9.04, 50.18)	(8.14, 49.35)
12	27.13	5.68	5.69	26.08	24.57
	(15.84, 36.87)	(1.21, 19.14)	(2.44, 20.88)	(8.40, 45.55)	(8.57, 43.53)
16	27.22	5.80	6.21	25.54	25.10
	(15.25, 37.94)	(1.53, 18.98)	(3.15, 20.05)	(8.36, 45.12)	(8.60, 43.74)
20	27.25	5.79	6.33	25.05	26.26
	(14.67, 38.51)	(1.67, 18.65)	(3.46, 19.55)	(8.39, 45.11)	(8.89, 44.67)
24	27.96	5.69	6.21	24.54	26.61
	(14.41, 39.69)	(1.64, 18.12)	(3.46, 18.76)	(8.32, 44.81)	(8.87, 46.03)
28	28.52	5.57	6.24	24.28	26.50
	(14.32, 40.98)	(1.59, 17.63)	(3.50, 17.95)	(8.35, 44.32)	(9.14, 45.79)
30	28.65	5.56	6.32	24.16	26.57
	(14.27, 41.36)	(1.57, 17.42)	(3.48, 17.63)	(8.38, 44.55)	(9.29, 46.45)

Notes: FEVD of Private Investment from all shocks in the benchmark model in pre Great Moderation period data (1954-1978) identified with Identification Strategy 1. Median level and 68% confidence bands are reported.

Table 9: FEVD of Investment with Identification Strategy 2

Horizon	TFP	FTS	MP	SRatio	Residual
1	7.31 (0.34, 32.83)	15.18 (2.36, 51.54)	23.61 (2.62, 72.04)	12.34 (0.93, 38.08)	4.19 (0.52, 17.76)
4	23.55 (7.08, 47.50)	16.18 (2.99, 43.74)	19.95 (3.63, 50.98)	11.15 (2.71, 33.19)	5.66 (1.65, 21.85)
8	25.32 (5.24, 48.81)	11.75 (1.70, 36.50)	21.49 (3.10, 47.29)	11.89 (1.99, 35.21)	6.74 (1.19, 26.75)
12	27.06 (5.91, 51.14)	12.95 (2.90, 37.11)	18.40 (2.66, 43.81)	11.63 (1.70, 34.47)	7.25 (1.01, 26.05)
16	27.83 (6.77, 50.80)	13.59 (3.99, 37.90)	17.88 (2.81, 40.85)	11.92 (1.75, 33.98)	7.68 (1.02, 25.92)
20	28.17 (6.76, 49.62)	14.21 (4.90, 37.91)	18.46 (3.31, 39.49)	11.81 (2.00, 33.51)	7.71 (1.11, 25.81)
24	28.21 (7.02, 48.75)	14.39 (5.64, 38.18)	18.66 (3.72, 38.71)	11.85 (2.33, 33.02)	7.87 (1.23, 25.52)
28	27.92 (7.19, 48.00)	14.60 (6.23, 38.15)	18.54 (4.14, 38.14)	11.85 (2.65, 32.56)	8.00 (1.48, 25.38)
30	27.78 (7.21, 47.64)	14.64 (6.48, 38.15)	18.48 (4.25, 38.05)	11.81 (2.68, 32.34)	7.97 (1.59, 25.43)

Notes: FEVD of Private Investment from all shocks in the benchmark model identified with Identification Strategy 2. Median level and 68% confidence bands are reported.

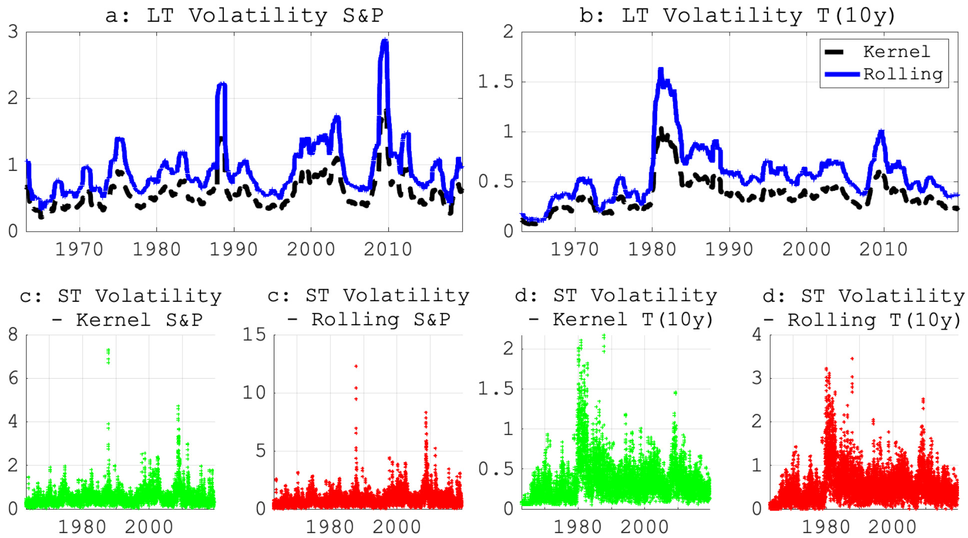
Table 10: FEVD of Investment with Identification Strategy 3

Horizon	TFP	FTS	MP	SRatio	Residual
1	4.05	14.09	39.70	6.25	2.61
	(0.13, 19.80)	(1.71, 58.41)	(8.94, 78.99)	(0.66, 32.25)	(0.45, 11.70)
4	28.01	24.99	17.91	9.59	5.12
	(7.74, 48.65)	(4.50, 50.14)	(4.23, 37.20)	(2.67, 27.08)	(1.11, 19.03)
8	33.34	24.37	17.36	10.51	5.62
	(7.39, 51.82)	(4.35, 43.88)	(3.80, 31.07)	(1.97, 29.27)	(1.18, 23.71)
12	34.61	25.82	14.18	11.46	5.88
	(8.40, 55.76)	(5.25, 43.42)	(3.37, 26.43)	(2.10, 30.79)	(1.22, 24.93)
16	34.97	26.54	12.75	11.99	5.89
	(9.14, 56.37)	(6.06, 43.17)	(3.40, 23.90)	(2.26, 31.37)	(1.16, 25.32)
20	34.64	27.22	12.39	12.20	6.01
	(9.26, 56.75)	(6.59, 42.86)	(3.40, 23.06)	(2.23, 31.53)	(1.33, 25.39)
24	34.05	27.37	12.26	12.23	6.15
	(9.16, 56.36)	(7.13, 42.74)	(3.36, 22.74)	(2.35, 31.60)	(1.39, 24.91)
28	33.74	27.55	12.10	12.53	6.37
	(9.30, 56.15)	(7.62, 42.60)	(3.33, 22.45)	(2.67, 31.63)	(1.66, 24.61)
30	33.70	27.35	12.01	12.58	6.45
	(9.50, 55.90)	(7.90, 42.57)	(3.31, 22.28)	(2.83, 31.61)	(1.72, 24.47)

Notes: FEVD of Private Investment from all shocks in the benchmark model identified with Identification Strategy 3. Median level and 68% confidence bands are reported.

D Figures

Figure 23: Volatility from Kernel and Rolling days method



Notes: Long term (LT) and Short term (ST) conditional volatility, variance, correlation and covariance for daily returns on S&P 500 and US 10 year Treasury bonds. The long run variances are calculated by using a backward looking kernel of 250 days, whereas short run variances are based on backward looking kernel of 5 days. The rolling days volatility calculation puts equal weight on past 250 days for Long run and on past 5 days for Short run calculation. See Appendix B.1 for a detailed methodology.

Figure 24: Threshold approach to FTS

Notes: Cumulative probability density of observation (in circles) and time-varying threshold (solid line) on days that are considered as FTS (i.e. when $Pr_{obs} < Pr_{ths}$). The threshold is set below 'kappa' times the conditional volatility of asset returns $r_t = (r_{e,t}, -r_{b,t})$. Parentheses in chart titles signify the percentage of total days from 1965 to 2019 that count as FTS for a particular choice of threshold criteria (or kappa). Y-axis: the probability of each FTS event, X-axis: date (in years).

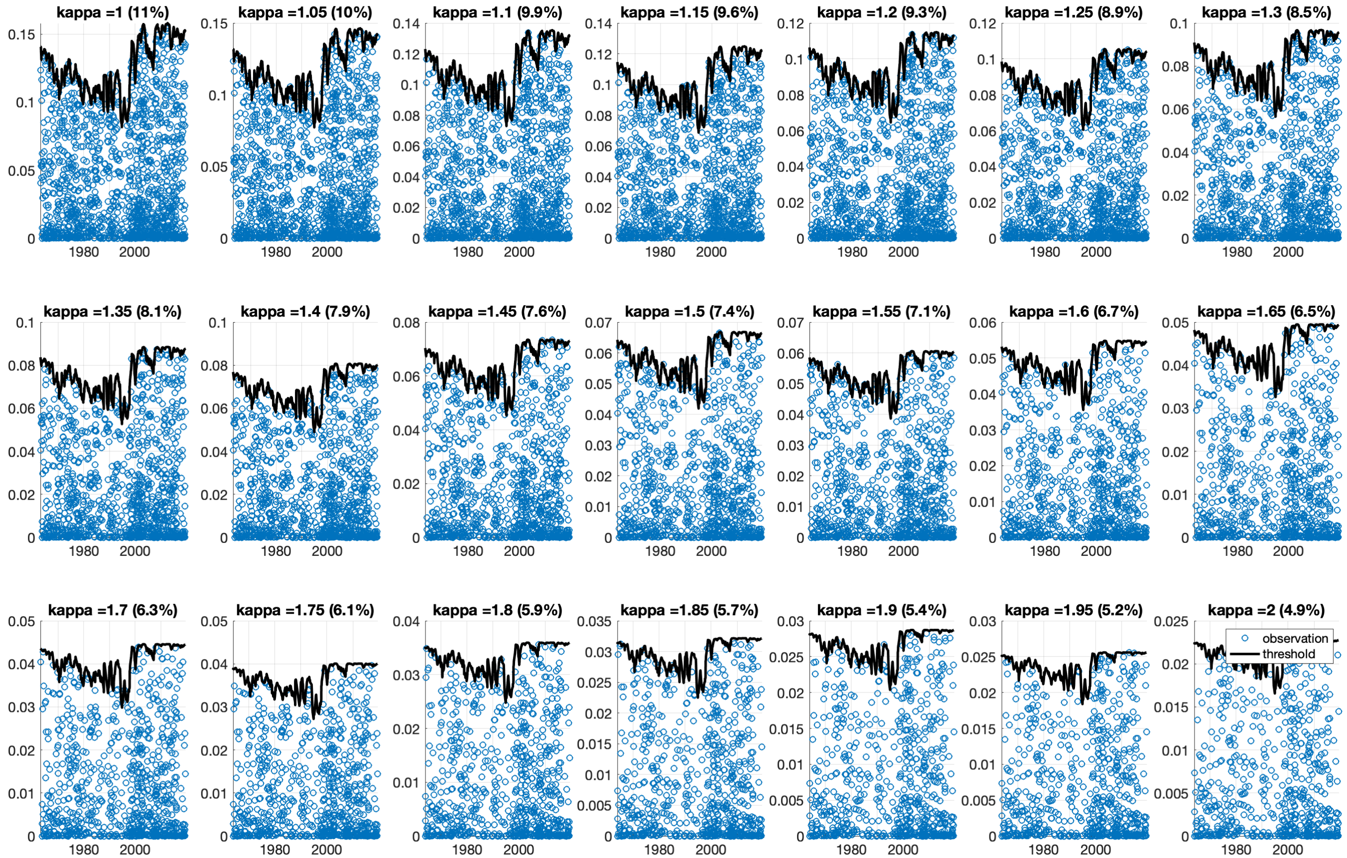


Figure 25: Ordinal index approach to FTS

Notes: FTS probability of observations whose Ordinal rank is above the rank of chosen threshold k. Varying levels of threshold are set by choosing different k, or the 3rd weak feature of FTS, which requires the short to long run ratio of stock return volatility on FTS day to be greater than k, s.t $k > 1$. Y-axis: the probability of each FTS event, X-axis: date (in years).

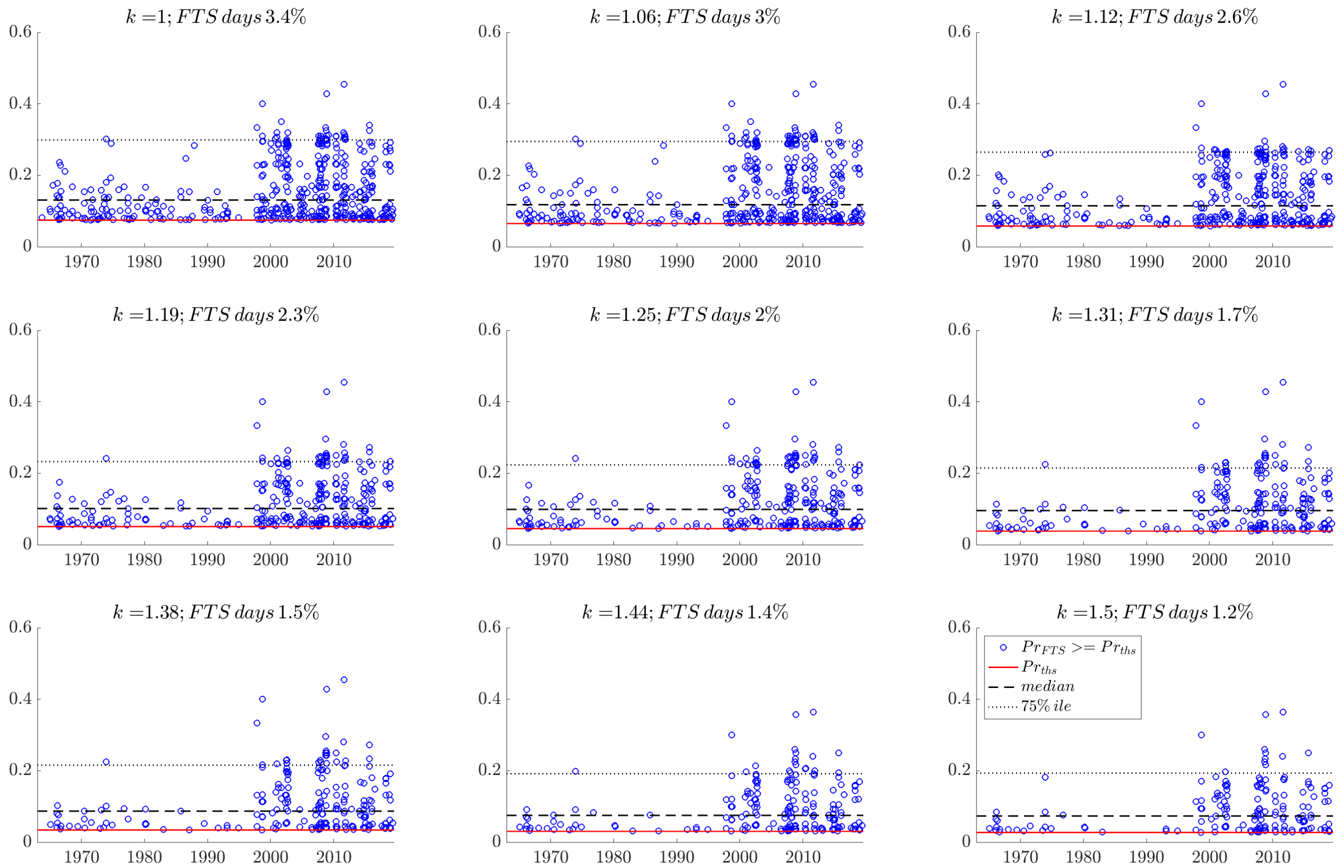
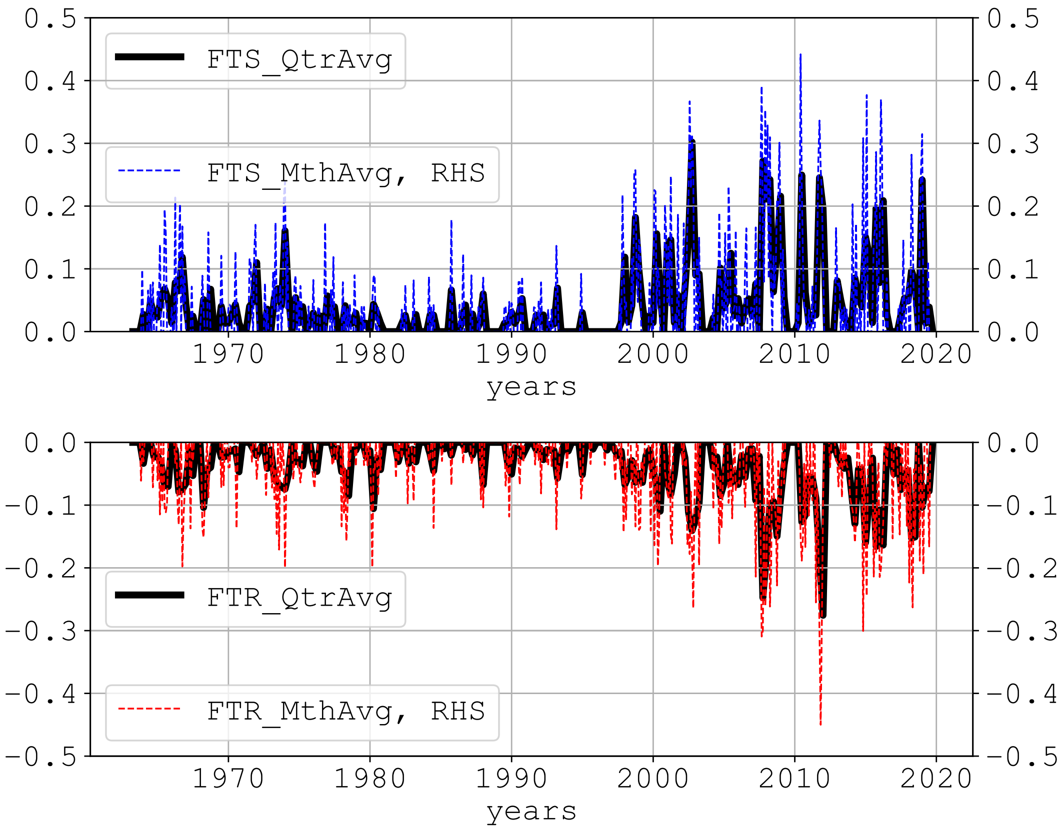
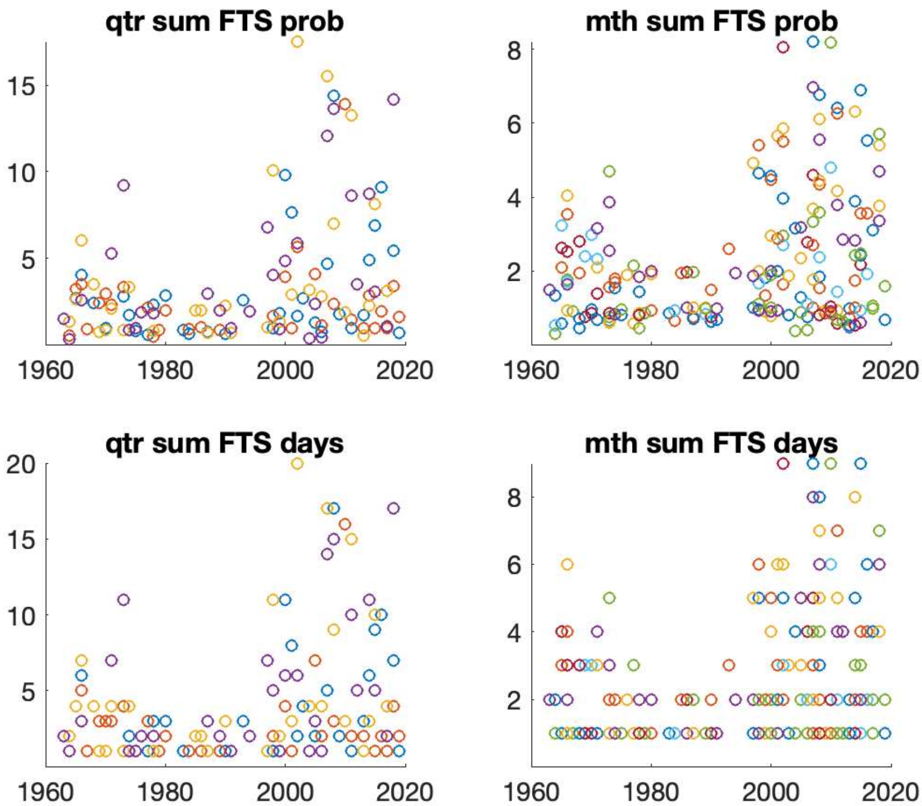


Figure 26: FTS and FTR shocks from Ordinal index method



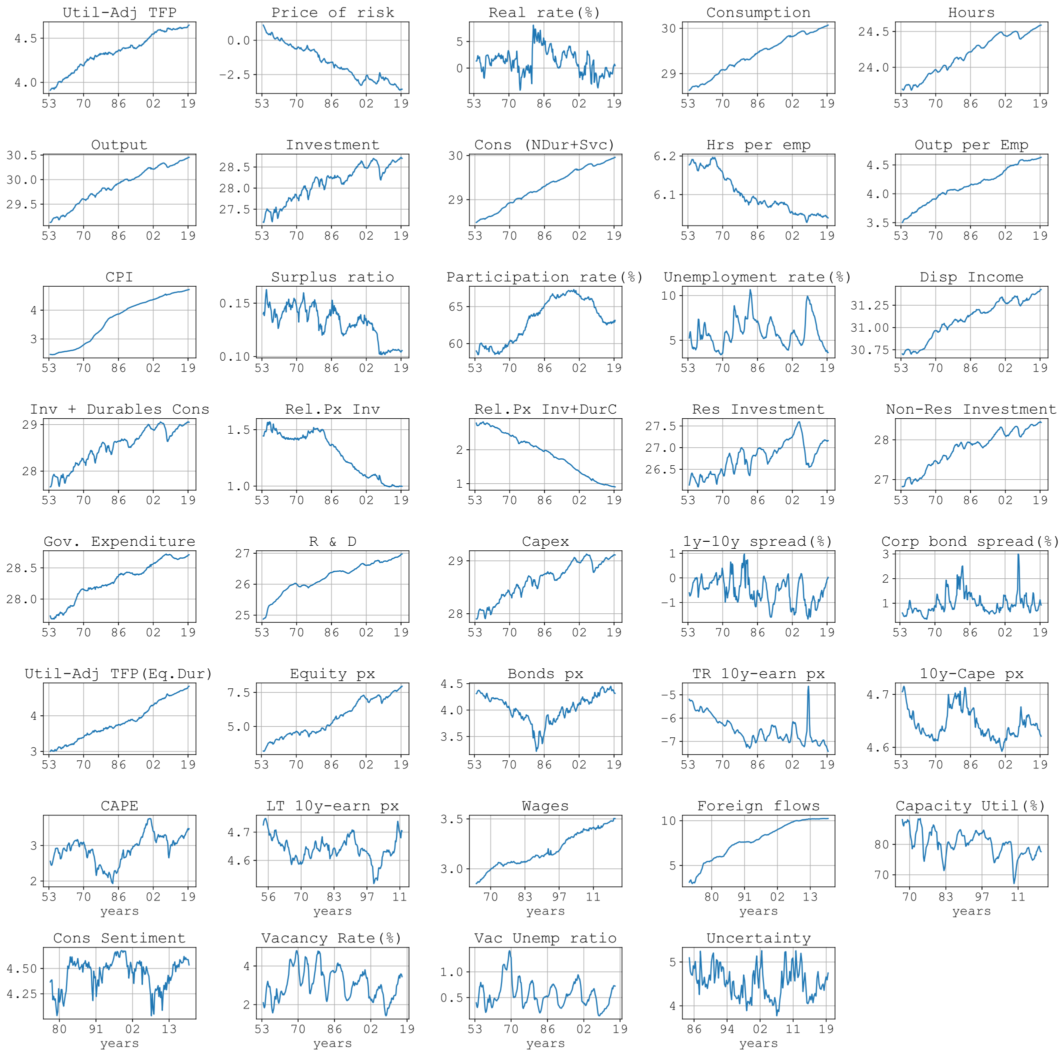
Notes: Quarterly and monthly average of FTS and FTR probability calculated from Ordinal index method discussed in Appendix B.3 with k equal to 1.

Figure 27: Frequency and Likelihood of Flight to Safety days II



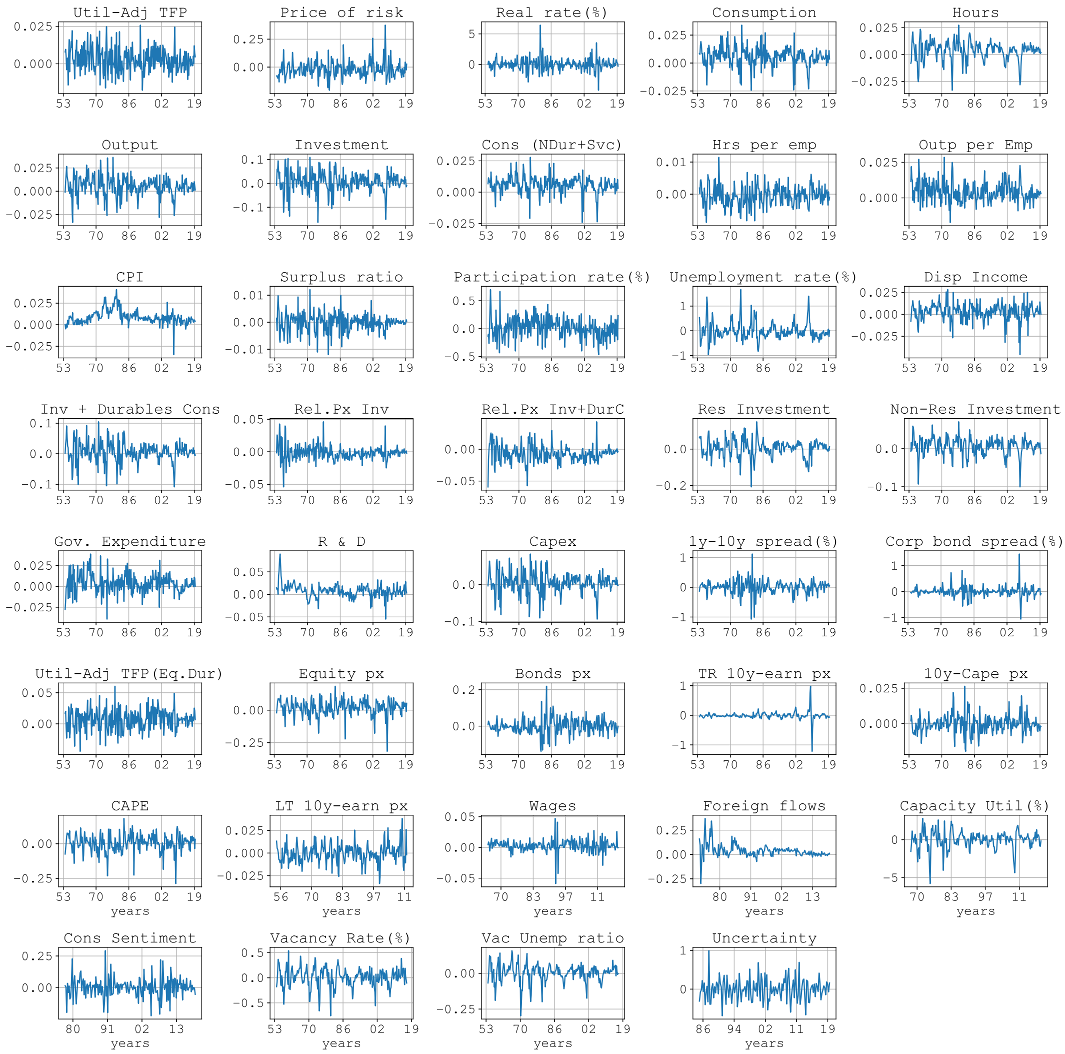
Notes: Aggregated Likelihood (prob) & frequency (days) of Flight to Safety (FTS). Aggregated by month (mth) & quarter (qtr) from 1963 to 2019. FTS days are calculated by Ordinal index approach (see Appendix B.3), for $k = 1.25$. Aggregated likelihood, or strength of FTS, for each month or quarter in the studied period is calculated by adding the cdf probability value for each FTS day during that period.

Figure 28: Time-series plots of US macroeconomic variables



Notes : Cons(NDur+Svc) is the Non-surables and Services consumption, Rel.Px Inv is relative price of Investment in terms of the price of Consumption. Rel.Px Inv+Dur is relative price of Investment and Durables consumption in terms of price of Services+Non durables consumption. px stands for price, Cons for consumption, Inv for investment, Res for residential, emp for employee, vac for vacancy, TR for total return, earn for earnings, Cape for Cyclical adjusted price to earnings. Except for ratios and series labelled in %, all other time series are in logs. X-axis: years in last 2 digits (YY) format.

Figure 29: First-differenced plots of US macroeconomic variables



Notes : Cons(NDur+Svc) is the Non-surables and Services consumption, Rel.Px Inv is relative price of Investment in terms of the price of Consumption. Rel.Px Inv+Dur is relative price of Investment and Durables consumption in terms of price of Services+Non durables consumption. px stands for price, Cons for consumption, Inv for investment, Res for residential, emp for employee, vac for vacancy, TR for total return, earn for earnings, Cape for Cyclical adjusted price to earnings. Except for ratios and series labelled in %, all other time series are in logs. X-axis: years in last 2 digits (YY) format.