Uncertainty and investment in Japan's 'Lost Decade'

Luke Meehan*

19 March 2015

Abstract

Does uncertainty matter for Japanese investment? Does this impact vary over time, particularly in periods of crisis? Could uncertainty shocks have contributed to the 'Lost Decade'? Variations in private fixed investment are perhaps the key driver of Japanese economic fluctuations, most notably the 'Lost Decade' (Horioka 2006). Real options theory suggests increases in uncertainty should have negative impacts on investment. Bloom et al. (2012) suggest the non-linear impacts of these shocks are key drivers of investment activity and the business cycle. This paper uses time-varying parameter VAR methods augmented with non-linear volatility to evaluate two models of investment with three different uncertainty instruments. Domestic uncertainty shocks have significant short-term depressive effects on investment throughout 1990-2011, with medium-term effects rebounding positively before returning to trend - the canonical 'wait-and-see' effects associated with real options. These results suggest uncertainty shocks were not directly culpable in Japan's 'Lost Decade'. The evidence that the impacts of uncertainty shocks are linear across time and magnitude is novel and demonstrates the importance of time-varying estimation techniques.

*PhD Candidate, Crawford School of Public Policy, Australian National University, currently a Visiting Scholar at the Graduate School of Economics, The University of Tokyo. This version prepared in submission to the 4 th Ifo Conference on "Macroeconomics and Survey Data". I would like to thank my advisers Jenny Corbett, Ippei Fujiwara and Renee McKibbin for their support; Yasuyuki Sawada, Yasuo Hirose, Naoyuki Yoshino, Kosuke Aoki, IDEC and ACDE Seminar participants for helpful comments; Jouchi Nakajima for MATLAB codes; and gratefully acknowledge financial support from the Australia-Japan Business Cooperation Council and The Japan Foundation Fellowship for Japanese Studies. All codes and data available at the Crawford PhD homepage or from luke.meehan@anu.edu.au

1 Introduction

Does uncertainty matter for Japanese investment? Does this impact vary over time, particularly in periods of crisis? Could uncertainty shocks have contributed to the 'Lost Decade'? The long-term down trend of modern Japanese investment displays repeated short-term falls followed by recoveries that fail to return to level. This paper finds that uncertainty shocks caused Japanese private fixed investment to fall steeply in the short-term, rebound, overshoot and return to trend in the the medium term throughout the 'Lost Decade' period.

Horioka (2006) identified low levels of private fixed investment as the underlying cause of the 'Lost Decade', together with inventory investment and government investment. His finding regarding private fixed investment was particularly strong in terms of a plummeting rate of growth. These low levels of investment and associated high levels of corporate cash holdings remain imperfectly understood in the literature (Kasahara, Sawada & Suzuki, 2011).

Politicians, economists and policymakers frequently identified uncertainty shocks as culpable for the falls in output and investment during the great recession. Larry Summers (March 2009) summarised the issue well: "...unresolved uncertainty can be a major inhibitor of investment. If energy prices will trend higher, you invest one way; if energy prices will be lower, you invest a different way. But if you don't know what prices will do, often you do not invest at all." A key paper in support of these hypotheses is that by Bloom (2009), whose time-series analysis and real business cycle models indicated uncertainty could be a primary driver of business cycles.

Real options theory suggests increases in uncertainty should have negative impacts on investment. Bloom et al (2012) suggest the non-linear impacts of these shocks are key drivers of investment activity and the business cycle. Theoretically, these wait-and-see shocks should drive investment temporarily lower, followed by a heightened recovery. Recent work by Bachmann, Elstner and Sims (2013) throws doubt on this theory by showing that short-term uncertainty innovations have long-term impacts in Germany and the US. Their work supports that conducted by Ogawa and Suzuki (2000) who found significant negative impact of uncertainty shocks in Japan on annual panel data. Choi (2013) further finds that the empirics in Bloom (2009) may be sample period dependent.

I compare the theoretical impacts of real-options-driven uncertainty to investment using time-varying parameter VAR models with stochastic volatility (TVP-VAR). The econometric analysis considers five hypotheses concerning private fixed investment in Japan over the period 1990-2011: 1) uncertainty has some non-zero impact on investment, 2) that an increase in uncertainty leads to a short-term fall in investment, 3) an increase in uncertainty leads to a medium-term increase in investment, 4) these impacts vary over time and 5) these impacts are greater during periods of peak uncertainty.

All results are consistent in confirming hypotheses 1, 2 and 3. Hypotheses 4 and 5 find little support in the data. The rest of the paper is organised as follows: Section 2 discusses the motivation for this investigation into uncertainty, 3 discusses the real options effects of uncertainty shocks, 4 considers the state-of-the-art in Japanese investment research, 5 discusses two small models of investment, 6 presents two uncertainty measures and data sources, 7 discusses the time-varying parameter model used, 8 interprets the estimation results and 9 discuss the implications for future research.

2 Why uncertainty?

Uncertainty has spent the last decade competing with 'austerity', 'crisis' and 'quantitative easing' for the title of 'Macro Buzzword de Jour'. The impact of uncertainty shocks is a controversial topic in the macroeconomics literature[1]. This is due to both the difficulty in separating the impact of changes in anticipated returns from mean-preserving spreads in anticipated returns distributions (or 'Panglossian' uncertainty shocks) and due to the difficulty in accounting for the time-varying impact of uncertainty shocks.

Whilst the empiric literature remains uncertain about the impacts of increases in uncertainty, the proposed depressive role of uncertainty remains extremely popular in the policy arena. Central bankers "A black cloud of uncertainty is hanging over investment" (Mervyn King, Bank of England, 2012), IMF economists "Uncertainty is largely behind the dramatic collapse in demand," (Owen Blanchard, IMF, 2009) and politicians (Barack Obama, USA) "[policy] uncertainty is already having an effect", have consistently identified uncertainty as a vital macroeconomic shock with a negative influence on activity.

Perhaps a portion of the attractiveness of uncertainty as a driving force is its contemporaneity with episodes of sudden recession. Figure 1 shows the levels of the Japanese private fixed investment, in the form of machinery purchases against the calculated Tankan forecaster dispersion data, with an apparent negative correlation supporting such concepts.

But these shocks are also associated with real falls in global activity. Trade, currency, investment, financing and demand all decline post-shock (Fry et al. 2011). Disentangling a mean-preserving shock to uncertainty requires careful, theory-consistent, analysis.

3 How uncertainty?

This section briefly outlines a theoretical relationship between investment and uncertainty which motivates substantial recent micro- and macroeconomic investigation - notably the literature following Bloom (2009). The theory is known as the 'real options' theory of investment, and it anticipates two epiphenomena in 'wait-and-see' and 'caution'. In discussing these epiphenomena, this section provides a benchmark for estimation and motivates our use of time-varying VAR models.

[1] see Mike Konczal of the Roosevelt Institute: http://www.nextnewdeal.net/rortybomb/what-economic-policy-uncertainty-index-really-telling-us

Real options investment theory emerged from the empirical failures of Tobin's q and Jorgensen's neoclassical approaches. Strongly associated with the 1996 book 'Investment and Uncertainty' by Dixit and Pyndick, as well as Abel and Eberley's (1996) work, real options theory is based on three key features of investment decisions. Firstly, most capital investments are to some non-trivial degree irreversible – sunk costs exists. Secondly, investment decisions are made in the reality of uncertainty in terms of future returns – outcomes are probabilistic. Thirdly, investors control the timing of investments – postponement to acquire information is possible.

Real options theory associates innovations to uncertainty with 'wait-and-see' and 'caution' effects. 'Wait-and-see' refers to the tendency of firms, when suddenly in a more uncertain environment, to delay expenditure. 'Caution' effects occur when uncertainty increases, rendering firms less sensitive to other changes, such as input prices and demand.

'Wait-and-see' effects are simple and intuitively satisfying, being a consequence of the option approach in which an investment decision is an opportunity to purchase an asset at different points in time. The optimal investment policy balances the value of waiting for new information with the cost of postponing the investment in terms of forgone returns. When a firm makes the decision to invest, it forces the expiration of the option to wait for new information regarding the investment return mean and distribution. As Abel and Eberley (1996) note, the anticipated return to investment must therefore exceed the purchase and installation costs by an amount equal to the value of keeping the option alive. If there is a mean-preserving spread in the distribution of returns, the option value of waiting increases and current-period investment falls. From Bachmann et al. (2013), "why pay a fixed cost now when a highly uncertain future means one will likely have to pay the fixed cost again?"

'Caution' effects are similarly straightforward. If a firm need weigh up several factors in making a decision, then any large increase in one factor will comparatively decrease the importance of all others; a large increase in the cost of capital – as is demonstrated during credit-crunch periods – may well decrease a firm's sensitivity to labour cost changes. If the option value of uncertainty is a factor in a firm's decisions, then uncertainty spikes will lower price-sensitivity in other factors.

These real options effects are the basis of the modelling of uncertainty-driven business cycles by Bloom (2009) and Bloom et al. (2012). This body of work argues positive innovations to uncertainty lead to short-run falls in investment and hiring, in turn leading to short-term falls in activity. When the waiting period is finished, pent-up demand leads to a medium-term increase in activity, as depicted in by the capital responses in Figure 2.

Bloom (2009) and Bloom et al. (2012) implement RBC and DSGE models, respectively, augmented with uncertainty shocks. Bloom (2009) also implements a range of VARs evaluating the role for stock market volatility in driving US macroeconomic outcomes. These models indicate volatility shocks have short-term (less than 12 months) depressive impacts on industrial production, but medium-term (more than 12 months) positive impacts. These results fit the wait-and-see typification of uncertainty shocks well. Bloom et al. (2012) develop micro-level measures of uncertainty that are strongly counter-cyclical at the national and sector levels. Their simulations of uncertainty shocks show investment falling steeply in a short-term response, before recovery to a positive effect in the medium-term.

This time-varying nature of uncertainty is key to the relationship identified by Bloom (2009) between uncertainty and business cycles. But the non-linear nature of the relationship makes this stochastic volatility famously difficult to empirically evaluate. Testing of the relationship requires a method capable of allowing parameters to vary over time.

Two recent papers have tested the short-term fall, medium-term recovery result from Bloom (2009) and Bloom et al. (2012). Bachmann et al. (2013) test this on US and German data. Using business confidence survey data, they construct an uncertainty measure consisting of the degree of forecaster disagreement – a dispersion index. They further construct an aggregate dispersion index and a micro-level, sectoral robust index and find the measures are positively correlated with impacts on economic activity that are often statistically indistinguishable.

Bachmann et al. (2013) use two-variable SVARs to identify the impact of uncertainty on manufacturing production, general business activity and manufacturing employment. Their impulse response analysis indicates that uncertainty shocks have protracted negative impacts on economic activity that are quantitatively small on impact. They further show that innovations to business confidence (a strongly pro-cyclical measure) have similar impacts to uncertainty innovations. An attempt to identify the time-varying impact of uncertainty shocks is made via Blanchard-Quah decomposition restrictions, which has similar results.

The work of Bachmann et al. (2013) could have been improved in three key areas. Firstly, the dependent variable choices – activity, employment and production – are open to debate. Employment is famously sticky, particularly in Germany - see Siebert (2005). Production may also be a function of existing orders rather than anticipated business conditions and their combined impact may render general business activity comparably murky. Moreover, the real options literature deals particularly with investment as this may be both easier to alter than staffing or extant orders as well as more susceptible to changes in anticipated returns (Dixit and Pyndick 1996).

Second is the absence of effective time-varying analysis: the SVAR impulse responses are based on coefficient averages throughout the sample period, not at periods of peak uncertainty. Finally, the use of more global uncertainty measures may have allowed business-cycle exogenous analysis.

Choi (2013) repeats Bloom's (2009) time-series analysis with sub-period divisions. Division of the VAR data into pre- and post-1982 delivers markedly different results. The earlier period displays theoretically-familiar wait-and-see fall-rebound effects. Impulse responses during the post-1982 period show no short-term impact and positive medium-term impacts. These contra-theory results suggest a need for further investigation.

4 Japanese private fixed investment

The choice of Japan as the focal point of this analysis is motivated by the global importance of the Japanese economy, the key role of Japanese Private Fixed Investment in the 'Lost Decade' (Horioka, 2006) and the similarity between Bloom's simulated 'wait-and-see' capital response to uncertainty shocks (as per Figure 2) and the Japanese investment time-series in Figure 1.

With specific regard to Japan, Horioka (2006) identified low levels of private fixed investment as the underlying cause of the 'Lost Decade', together with inventory investment and government investment. His finding regarding private fixed investment was particularly strong in terms of a plummeting rate of growth.

There is a deep literature using Tobin's q and neoclassical models to investigate the cause of these falls in investment. The model developed by Kiyotaki & West (1997) was motivated by Japan's post-bubble fall in output and places private fixed investment as a major constituent of business cycle variations, albeit one that responds only to output and cost-of-capital variations. Ando (1998) and Bayoumi (2001) discuss the slowdown as a consequence of a low return to further capital investment following previous over-investment, although this gives primacy to wealth effects by assuming an absence of wealth-creating investment opportunities. Hayashi and Prescott (2002) conduct a growth accounting exercise and find that low investment was a causal factor which was in turn driven by low TFP, but fail to unpack what the relevant constituents of TFP may be (Hoshi & Kashyap, 2004). More recently, Tyers & Zhang (2011) attempt to explain the declining investment share of GDP in a multi-sector dynamic model and in turn Japan's economic recovery of 2002-2007, finding an important role for the impact of an ageing population. This finding is consistent with the broad, long-term downtrend in investment displayed in Figure 1.

An important field of Japanese fixed investment research places financing constraints at the centre of investment investigation. Financing theories of investment focus primarily on the degree to which private fixed investment is aided or constrained by the availability of liquid investment capital. These theories also attempt to explain the empiric importance of cashflow to investment; the absence of which is a major failing of neoclassical theories (Caballero 1999). The Japanese experience with financial excesses in the 1980s and financial crises in the 1990/2000 decades resulted in deep literature investigating the how these events may have driven private fixed investment and consequently business cycles. Hoshi, Kashyap and Scharfstein (1991) take advantage of the 'keiretsu' industrial organisation idiosyncrasies of Japan to evaluate the investment influence of reliable credit. They found support for a credit protection effect, with investment less sensitive to cashflow in keiretsu-protected firms. Kaplan and Zingales (1997) extend the cashflow discussion by noting the absence of theory or empiric evidence for investment-cashflow sensitivities to increase with financial constraints. Their paper - when considered with Hubbard's (1998) and Bernanke, Gertler and Gilchrist's (2000) provision of evidence and theory, respectively, of a preference to finance investment with internal than external funds - is a major motivator of this thesis' investigation into investment variations.

The current state-of-the-art in financing investment theory is demonstrated by Kasahara, Sawada and Suzuki (2011). Their dynamic structural model of the Japanese economy indicates that, following Japan's financial crisis of 1997, there was a sharp decline in bank loans to firms followed by a fall in corporate investment in 1998-9. They found support for the theories of low bank health leading to low firm investment and, accordingly, for some exogenous financial constraint to indicate low firm investment. Their model under-predicts investment of low TFP firms and over predicts investment of high TFP firms, potentially signalling a channel for non-fundamentals based decision making. The authors note the potential for further mechanisms in the paper: "The large variance of idiosyncratic shocks indicates that there are unobserved factors for investment that are not fully explained by the observed state variables in the model, which is not surprising because empirically explaining a large portion of the cross-sectional variation in investment by observed variables has been found to be difficult in the literature."

Little research has been conducted into the role uncertainty may have played in the post-bubble falls in Japanese investment. Ogawa and Suzuki (2000) evaluate the conditional standard deviation in the growth rate of sales as a driver of Japanese manufacturing firms' investment. They find uncertainty has a significant negative impact on investment which is closely related to the degree of irreversibility of capital. Their panel analysis is unable to decompose impacts of uncertainty across time and magnitude and may suffer from using measures of uncertainty partially endogenous to Japanese business-cycles.

5 Models

This section details the two theoretical models upon which the uncertainty-investment empiric analysis is based.

The first model (Model 1) is a simple two-variable model as per Bachmann et al (2013). This pure real options model suggests that investment can be responsive to only itself and an uncertainty shock:

$$I_t = I_{t-s} + Unc_t \tag{1}$$

The TVP-VAR analysis of Model 1 is ordered as $I_{t,}Unc_t$.

Any simple 2-variable model cannot be expected to evaluate the impact of long-term trends and may well suffer from omitted variable bias. An alternative model which is able to consider the general-equilibrium nature of investment decisions would be optimal. But these models are invariably large-scale and unable to be evaluated given current TVP-VAR software. Candidate models must therefore be as closely GE-compliant as possible, whilst minimising parameter use.

I use an investment adjustment-cost model (Model 2), widely used in the DSGE literature from Christiano et al. (2005). Eberley et al. (2012) show this model can be re-written with investment/capital ratio as a function of its own lag, average Tobin's Q and a shock:

$$I_t = f(I_{t-s}, K_t, V_t, z_t) \tag{2}$$

where $K_t$is the capital stock of the firm at time t, V_t is the value of the firm and $z_t$is some shock to total factor productivity. This paper allows uncertainty to enter through the TFP-shock term z. The model is evaluated at the aggregate level, with the Nikkei 225 Index acting as an aggregate firm value instrument, noting that equity indices represent the discounted value of anticipated returns.

The TVP-VAR analysis of Model 2 is ordered as I_t, K_t, V_t, z_t. This ordering broadly indicates that investment does not respond fully to capital, whereas capital does fully respond to investment. This is problematic, particularly as the Christiano et al (2005) treatment of investment explicitly holds investment to be the means by which capital is optimised, as opposed to driving activity. The empiric weakness of such assumptions (from Blanchard (1986b) '... it is well known that to get the user cost to appear at all in the investment equation, one has to display more than the usual amount of econometric ingenuity') motivated a long empiric literature on managerial decisions (for instance Brounen et al. (2004), Hallikainen (2006) and the Japanese case presented by Shinoda (2010)) where managerial investment decisions are based on capital availability and simple payback accounting.

A second justification for this controversial ordering concerns the specific nature of Japanese corporate asset holdings in the post-1990 period. Koo (1999) notes the very high levels of capital holdings by Japanese companies in during this period were heavily weighted by 'bubbly' assets, particularly land and stocks. These asset holdings were not typically held for the purpose of conducting business, but often for speculative or corporate alignment (the so-called cross-holdings of company shares). As such, they may not be a primary driver of presumably productive investment (as per the data definition in Section 6.4).

6 Uncertainty measures and data

This section discusses the selection logic behind the variables used in my empiric analysis. It also identifies data treatments and sources.

6.1 Three measures of uncertainty

Precise data on the individual uncertainty distributions of decision-makers is unavailable for Japanese enterprises. The use of a proxy for these distributions is necessary; these are most accessible in aggregate. But all empiric work is weakened by use of proxies, with vulnerabilities stemming from weakly-associated proxies, system endogeneity or omitted variable bias. This paper takes these vulnerabilities seriously and uses conceptually, sectorally and geographically separate proxies for uncertainty.

Firstly, I follow Bachmann et al. (2013) in the construction of an uncertainty measure based on the Bank of Japan's Short-term Economic Survey of Enterprises in Japan, or 'Tankan': the standard deviation of a Tankan diffusion measure. This measure represents the degree of disagreement between managers of Japanese firms as to their 6-month forecast of business conditions. This measure is selected as a measure robust to the 'weakly associated proxy' vulnerability. The sample size, history and external weight placed upon the Tankan Index suggests that it will be strongly associated with actual business uncertainty. But a diffusion measure may represent naturally heterogeneous variation in opinions (i.e. from sectoral variations) and therefore be susceptible to omitted variable bias.

In order to move into a more 'pure' uncertainty space, I investigate the Chicago Board Options Exchange Market Volatility Index (VIX) - a popular measure of the implied volatility of S&P 500 index options. Widely used in the financial uncertainty literature it represents a measure of the US equity market's expectation of stock market volatility over the next 30 day period. This measure is chosen for its resilience to endogeneity criticisms, but due to separation in geography and economic systems may be a weak instrument for firm-level uncertainty in Japan.

Finally, I repeat the uncertainty measure analysed by Ogawa and Suzuki (2000) - the rolling 1-year standard deviation in the growth of sales. Ogawa and Suzuki take the view that when the structure of the output market is imperfect, and thus firms face a downward-sloping demand curve, 'uncertainty' shocks may be demand shocks. They therefore argue sales growth volatility is an important component of the real uncertainty firms face. This inclusion of sales growth volatility aids this paper's analysis in several way. Most notably it is a backwards-looking measure, as opposed to the more forwards-looking VIX and Tankan frecaster dispersion measures. Its inclusion is appropriate and useful in the unclear decision environment of firm-level investment; whether managers are backwards- or forewards-looking is theoretically and empirically uncertain (see the empiric importance of lagged investment in driving investment in Eberley et al (2012) compared with the forward-looking modelling by Bloom et al. (2012)).

6.2 Tankan dispersion

The Tankan is a statistical survey of private enterprises conducted by the Bank of Japan. The survey aims to provide an accurate picture of business trends of enterprises in Japan, thereby contributing to the appropriate implementation of monetary policy and is conducted quarterly in March, June, September, and December. The population of the survey is approximately 210,000 private enterprises (excluding financial institutions) in Japan with at least 20 million yen in capital.

The Tankan has several notable strengths as an uncertainty measure, primarily its statistical coherency and reputation. In terms of reputation, the Tankan is one of the key financial measures in Japan and has substantial influence on asset prices and monetary policy. Its coherence is well-documented by Bank of

Japan records and has been imitated by Spain national statistics organisation. Further, the Tankan is widely used as a business confidence, and business cycle, measure in the macroeconomic literature on Japan.

The survey question of interest for this analysis is the first question in the 'Judgment Survey' section. In this section, responding enterprises are asked to choose one alternative among three as the best descriptor of prevailing conditions, excluding seasonal factors at the time of the survey and three months hence. The question of interest requests 'Judgement of general business conditions of the responding enterprise, primarily in light of individual profits.' Potential answers are: 1) Favorable. 2) Not so favorable. 3) Unfavorable.

The widely-reported 'Tankan Index' (see Bloomberg, 2012a, b) is the 'Business Conditions Diffusion Index'. This diffusion index is calculated by subtracting the percentage share of enterprises responding '(3) Unfavorable' from that of '(1) Favorable.' There is no weighting measure: each respondent has one 'vote'. Respondents answer both an 'Actual result' and a 'Forecast' question, where the forecast pertains to the next quarter's business conditions. As the literature frequently features forecaster dispersion as an uncertainty metric (Bachmann et al. (2013) I use 'Forecast' responses.

To transform this diffusion index into an uncertainty measure I undertake the standard method for evaluating response disagreement in the survey data literature by indexing 'Favourable' responses as +1 and 'Unfavourable' as -1, then calculating the cross-sectional standard deviation.

6.3 The Chicago Board of Exchange Volatility Index (VIX)

VIX is the ticker symbol for the Chicago Board Options Exchange (CBOE) volatility index, which represents market volatility expectations over the next thirty days, as well as the popular measure of implied volatility for the S&P 500 index option. Since its introduction in 1993, VIX has become a preferred forward-looking indicator of investor sentiment and market volatility, and is often referred to as the "investor fear gauge". It is derived without reference to restrictive option-pricing models.

6.4 Data sources

Data cover the period Q1:1990 - Q1:2011, the longest period available. This relatively short period is a result of VIX index data being available from 1990, and a change in the measurement and collation of Japanese private fixed investment limiting that data to Q1:2011. Regardless of availability this period is of substantial interest, being the two 'Lost Decade/s' post-bubble, and free of confounding factors in the destructive Tohoku earthquake of March 2011 and the novel policies of Abenomics.

Japanese Private Fixed Investment (JPFI) data are taken from the Economic and Social Research Institute of the Cabinet Office of Japan (ESRI) from the publication 'Orders Received for Machinery'. Data are from the sub-section 'Machinery Orders by Sectors, Sales and Remainders (Seasonally adjusted, Quarterly)' and represent private sector purchases. These data are used in calculations under the assumption that they are representative of fixed investment variations across the Japanese economy. The machinery classifications included are 'Boilers and power units', 'Heavy electrical machinery', 'Electronic and communication equipment', 'Industrial machinery', 'Metal cutting machines', 'Rolling machines', 'Motor vehicles (over 5000kg)' and 'Aircraft'.

Accumulated, seasonally adjusted, quarterly capital stock data are are sourced from Japan's Ministry of Finance 'Financial statistics of corporations by industry'. To limit multi-collinearity with machinery investment and the Nikkei 225, capital stock is defined as the sum of 'Cash and deposits', 'Bills and accounts receivable', 'Inventories', 'Finished goods and merchandise', 'Works in process', 'Raw materials and goods supplies', 'Bonds and debentures', 'Other securities', 'Land', 'Intangible fixed assets' and 'Construction in process'. Data are collected from all Japanese firms with capital assets in excess of 10 million yen, excluding the Finance and Insurance sectors.

Tankan data are from the Bank of Japan time-series 'Tankan' data release.

Nikkei 225 Index and VIX data are taken from Thomson Reuters' Datastream. VIX data considered in this study are the quarterly maxima of the daily VIX data. The quarterly maxima instead of the quarterly average are chosen to ensure differentiation between short periods of high uncertainty and prolonged periods of moderate uncertainty, the import of which is described in Bloom (2009).

Where appropriate, all data are seasonally adjusted using the X12 ARIMA method. Investment, Capital, Nikkei 225 are examined on first-differenced log-levels. Sales volatility, Tankan forecaster dispersion and VIX Index data are evaluated on levels.

7 Time-varying Parameter VAR

The time-varying nature of the impact of uncertainty and its stochastic volatility is key to the identification the impact of uncertainty on economic activity by Bloom et al. (2009, 2012). The steady-state of uncertainty is small, and so comparative statics exercises (Dixit and Pindyck 1996, Abel and Eberly 1999 or the CAPM work of Baum et al. (2008) tend to show little impact. This indicates that, whilst OLS/VAR methods are potentially useful, they will not identify the full impacts of individual variable innovations on the system as a whole.

As the multi-moment nature of uncertainty calls for a multivariate approach, the use of a multivariate vector autoregressive model which allows for time-varying parameters and stochastic volatility is indicated: a TVP-VAR as introduced by Primiceri (2005). A substantial theme in the macroeconomic literature is the allowance for 'structural breaks' in time-series analysis, where coefficients can change in value (Stock and Watson, 1996). TVP-VAR analysis is a per-period extension of structural break analysis. Such techniques do not appear to have previously been applied to the question of investment under uncertainty.

An historical problem with incorporating time-varying parameters into VARs was the proliferation-of-parameters concern, especially considering the already large size of most macroeconomic models. Allowing the error-covariance matrix to change over time with the incorporation of stochastic volatility increases the proliferation-of-parameters issue (see Koop and Korobilis (2010) for a full discussion). Bayesian methods utilising prior information allow for the shrinking of parameter influence (either via restrictions or shrinking towards zero).

7.1 Setup

Using the method and MATLAB coding made available by Nakajima Joichi (Nakajima (2011) – modifications to code and datasets available at the Luke Meehan doctoral student homepage at Crawford.anu.edu.au), consider the representation of a TVP-VAR model:

$$y_t = c_t + B_{1t}y_{t-1} + \ldots + B_{st}y_{t-s} + e_t$$

$$e_t \sim N(0, \Omega)$$

For $t = s+1, \ldots, n$ where y_t is a $(k*1)$ vector of observations, $B_{1t}, ..., B_{st}$ are $(k*k)$ time-varying coefficient matricies and Ω_t is a $(k*k)$ time-varying covariance matrix. As demonstrated by Primiceri (2005) a recursive identification is assumed where the simultaneous relations of the structural shock e_t are decomposed with $\Omega_t = A_t^{-1}\Sigma_t\Sigma_t A_t^{'-1}$, where $A_t$is a lower-triangular matrix with the diagonal elements equal to one, and $\Sigma_t = diag(\sigma_{1t}, \ldots, \sigma_{kt})$. This allows the covariance of the errors to vary in time.

By this definition, the model evaluates three time-varying parameters: $\beta_t, a_t$and h_t, where:

β_t is the stacked row vector $B_{1t}, \ldots, B_{st}$

$a_t = (a_{1t}, \ldots, a_{qt})'$ is the stacked row vector of the lower-triangular elements of A_t

$h_t = log(\sigma_{it}^2)$ allows volatility to follow a stochastic process.

These parameters follow a random walk process, so the three state equations and their error terms are:

$$\beta_{t+1} = \beta_t + u_{\beta t}$$

$$a_{t+1} = a_t + u_{at}$$

$$h_{t+1} = h_t + u_{ht}$$

$$\begin{pmatrix} e_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N \left(0 \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right)$$

for $t = s+1, \ldots, n$, with $e_t = A_t^{-1}\Sigma_t \epsilon_t$, where Σ_a and Σ_h are diagonal, $\beta_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0})$,$a_{s+1} \sim N(\mu_{a0}, \Sigma_{a0})$ and $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h0})$.

This setup implies several assumptions, the first being Cogley and Sargent's (2005) specification of A_t as a lower-triangular matrix with ones on the diagonal. In following Primiceri (2005) by allowing for time-variance this assumption allows recursive identification of the VAR system and is relatively standard in the literature. But as Chib, Nadari and Shephard (2006) note, this can lead to highly autocorrelated MCMC draws, requiring a large number of draws to achieve accurate estimates. This estimation uses 10,000 draws instead of the Chib, Nadari and Shephard algorithm: a choice justified by Figure 13, which demonstrates minimal draw autocorrelation and appropriately-shaped paramter distributions.

A second assumption is that the parameters follow a random walk. This no-trend assumption in the time-varying coefficient, simultaneous relations and volatility stacked vectors allows further parameter shrinkage and is not unreasonable given the samples' paths depicted in Figure 13. A third assumption is that Σ_a and Σ_h are diagonal, which is relatively standard in the literature (Cogley and Sargent 2005, Nakajima 2011).

7.2 Estimation

The Markov Chain Monte Carlo sampling algorithm used is the stochastic volatility variant of the Gibbs Sampler from Nakajima (2011).

Let $y = \{y_t\}_{t=1}^{n}$ and $\omega = (\Sigma_\beta, \Sigma_a, \Sigma_h)$. Given the data y the following MCMC algorithm samples from the posterior distribution $\pi(\beta, a, h, \omega | y)$:

1. Initialise β, a, h and ω
2. Sample $\beta | a, h, \Sigma_\beta, y$
3. Sample $\Sigma_\beta | \beta$
4. Sample $a | \beta, h, \Sigma_a, y$
5. Sample $\Sigma_a | a$
6. Sample $h | \beta, a, \Sigma_h, y$
7. Sample $\Sigma_h | h$
8. Repeat from 2.

7.2.1 β sampling

To sample β from the conditional posterior distribution, the state space model with respect to the state variable β is written as

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \epsilon_t$$

$$t = s + 1, \ldots, n$$

$$\beta_{t+1} = \beta_t + u_{\beta t}$$

$$t = s, \ldots, n - 1$$

where $\beta_s = \mu_{\beta 0}$, and $u_{\beta s} \sim N(0, \Sigma_{\beta 0})$.

The simulation smoother requires a more general-form state-space model as in de Jong and Shepard (1995):

$$y_t = X_t \beta + Z_t \alpha_t + G_t u_t$$

$$t = 1, \ldots, n$$

$$\alpha_{t+1} = T_t \alpha_t + H_t u_t$$

$$t = 0, \ldots, n - 1$$

where $\alpha_0 = 0$,$u_t \sim N(0, I)$ and $G_t H_t^{'} = O$. The simulation smoother runs as below, with variables corresponding with (3) and (4) and where k_β is the number of rows in β:

$$X_t \beta = 0_k$$

$$Z_t = X_t$$

$$G_t = (A_t^{-1} \Sigma_t \epsilon_t, O_{k\beta})$$

$$T_t = I_{k\beta}$$

$$H_t = (O_k, \Sigma_\beta^{1/2})$$

$$H_0 = (O_k, \Sigma_{\beta 0}^{1/2})$$

7.2.2 a sampling

To sample a from the conditional posterior distribution, the state space model with respect to a is written for $t = s+1, ..., n$ where k_a is the number of rows in a_t:

$$\hat{y}_t = \hat{X}_t a_t + \Sigma_t \epsilon_t$$

$$t = s+1, \dots, n$$

$$a_{t+1} = a_t + u_{at}$$

$$t = s, \dots, n-1$$

where $a_s = \mu_{a0}, u_{as} \sim N(0, \Sigma_{a0})$,$y_t = y_t\hat{} - X_t\beta_t$ and

$$\hat{X}_t = \begin{pmatrix} 0 & \dots & & & & & & 0 \\ -\hat{y}_{1t} & 0 & 0 & \dots & & & & \vdots \\ 0 & -\hat{y}_{1t} & -\hat{y}_{2t} & 0 & \dots & & & \\ 0 & & & -\hat{y}_{1t} & \dots & & & \\ \vdots & & & & \ddots & 0 & \dots & 0 \\ 0 & \dots & & & 0 & -\hat{y}_{1t} & \dots & -\hat{y}_{k-1,t} \end{pmatrix}$$

The simulation smoother with respect to a has correspondences:

$$X_t\beta = 0_k$$

$$Z_t = \hat{X}_t$$

$$G_t = (\Sigma_t, O_{ka})$$

$$T_t = I_{ka}$$

$$H_t = (O_k, \Sigma_a^{1/2})$$

$$H_0 = (O_k, \Sigma_{a0}^{1/2})$$

7.2.3 h sampling

For stochastic volatility, the inference for $\{h_{jt}\}_{t=s+1}^{n}$ is made seperately for $j(=1,\ldots,k)$ as per the assumption that Σ_h and Σ_{h0} are diagonal matricies. Let y^*_{it} denote the i-th element of $A_t\hat{y}_t$, then:

$$y^*_{it} = exp(h_{it}/2)\epsilon_{it},$$

$$t = s+1,\ldots,n$$

$$h_{i,t+1} = h_{it} + \eta_{it}$$

$$t = s,\ldots,n-1$$

$$\begin{pmatrix} \epsilon_{it} \\ \eta_{it} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 \\ 0 & v_i^2 \end{pmatrix}\right)$$

where $\eta_{it} \sim N(0, v_{i0}^2)$ and v_i^2 and v_{i0}^2 are the i-th diagonal elements of Σ_h and Σ_{h0}, respectively, and η_{it} is the i-th elements of u_{ht}. The sampling of $(h_{i,s+1},\ldots,h_{in})$ is per Appendix B in Nakajima (2011).

7.2.4 ω sampling

Sampling ω (or Σ_β, Σ_a and Σ_h), from its conditional posterior distribution is conducted seperately for each term as per their specified prior distributions. For Σ_β the prior is assumed as $\Sigma_\beta \sim InverseWishart(v_0, \Omega_0^{-1})$

$$\pi(\Sigma_\beta|\beta) \propto |\Sigma_\beta|^{-\frac{v_0+p+1}{2}} exp\{-\frac{1}{2}tr(\Omega_0\Sigma_\beta^{-1}\} * \prod_{t=1}^{n-1} \frac{1}{|\Sigma_\beta|^{1/2}} exp\{-\frac{1}{2}tr(\hat{\Omega}\Sigma_\beta^{-1})\}$$

where

$$\hat{v} = v_0 + n - 1$$

$$\hat{\Omega} = \Omega_0 + \sum_{t=1}^{n-1}(\beta_{t+1}-\beta_t)(\beta_{t+1}-\beta_t)'$$

7.3 Simulation

To compute the posterior estimates Ie draw 50,000 samples after a 5,000 sample burn-in period. Two lags are used for in all VAR and TVP-VAR estimations, as indicated by AIC. The following priors are assumed for the i-th diagonals of the covariance matrices:

$$(\Sigma_\beta)_i^{-2} \sim InverseWishart(25, 10^{-4}I)$$

$$(\Sigma_a)_i^{-2} \sim Gamma(4, 10^{-4})$$

$$(\Sigma_h)_i^{-2} \sim Gamma(25, 10^{-4})$$

Figure 13 displays the estimation results from one typical TVP-VAR analysis. These results show the MCMC algorithm is functioning efficiently, covering all parameter distributions with minimal residual autocorrelation.

8 Results

This section discusses the TVP-VAR impulse responses from Model 1 (2-variable as per Bachmann et al. (2013)) and Model 2 (4-variable as per Eberley et al. (2012) and (Christiano et al. (2005)) analyses for all three uncertainty specifications: Tankan dispersion, VIX and sales growth volatility.

As these are time-varying estimates, a decision must be made as to from which time an impulse is to be simulated. This paper's motivating questions suggest that shocks be simulated generally across the estimation period, at the beginning of the 'Lost Decade' and at periods of unusually high and unusually low volatility. Consequently, I gather impulse responses on two-variable Model 1 system at 30%, 60% and 90% of the sample period, in order to judge the general impact of uncertainty on investment. Model 2 impulse responses are gathered at periods of unusually high and unusually low equity market volatility that span the estimation period: High-{Q4:1990, Q3:1998, Q4:2008} and Low-{Q2:1992, Q1:2000, Q4:2007}.

Results are displayed in the Appendix. Note that the variable set {MCH, K, NKK, TNK, VIX, SALE} corresponds to private fixed investment (machinery) purchases, corporate capital stock, the Nikkei 225 Index, the Tankan forecast dispersion, quarterly maxima of the VIX Index and 1-year rolling Japanese corporate sales growth volatility.

The Tankan dispersion and sales growth volatility impulses in the estimation of Model 1 appear to generate investment activity which closely match the shape of the 'wait-and-see' platonic ideal of uncertainty shocks (those associated with BLoom's (2009) aggregate capital simulations in Figure 2). The shocks have an immediate negative impact which quickly recovers to positive levels: the real options' canonical drop, rebound and recover effects. These effects appear almost identical in magnitude and direction across the estimation period.

The impulses in the VIX uncertainty system have short-term depressive impacts, but varied medium-term imapcts on Japanese investment. Impulses at 30% of the sample have longer-term depressive impacts than at 60% or 90%, when a rebound-and-recover impact is visible.

The first general observation on the TVP-VAR impulse response estimations of the Eberley et al. (2012) and (Christiano et al. (2005) variable set is that they contain more variation between periods than the 2-variable setup utilised by Bachmann et al. (2013) and Model 1 - particularly in the VIX-augmented system. This is to be anticipated given the estimation strategy, and is in fact a desired outcome of this form of Bayesian simulation. All variables are simulated conditional on other variables in the system, and by increasing the variable count the information density of coefficients are also increased. That the VIX system appears more irregular than either the Tankan or sales measures may be a meaningful artefact of the the dissimilarity between domestic and global uncertainty, or real and financial uncertainty, or it may be an indicator of poor algorithmic performance due to the relatively high skewness and kurtosis statistics of the VIX index (see Table 1). All VIX-augmented system results are interpreted with some caution.

The direction, shape and persistence of impulse-response diagrams are relatively consistent for domestic uncertainty systems, both in comparison with each other and across time. This is a substantial finding, in that there is little evidence that uncertainty innovations have greater impact on corporate investment activity during periods of unusually heightened or flattened uncertainty. To rephrase, the impacts of uncertainty appear linear in time and magnitude. This is a novel finding to the uncertainty and investment literature, which has broadly followed the assumption in Dixit and Pindyck's 1996 book and by Abel and Eberley (1999) that low levels of uncertainty have comparatively far smaller impacts than high levels. I find no evidence supporting this assumption, but rather that high levels of uncertainty have large impacts on activity simply because the levels of uncertainty are high.

All three Model 2 systems provide evidence broadly supporting the Tobin's Q theory of investment used by Christiano et al. (2005) and transformed to explain the lagged investment effect by Eberley et al. (2012), in that positive shocks to firm value in Nikkei 225 innovations have a consistent short-term positive impact on investment. Positive shocks to firm capital also have short-term positive impacts on investment.

The seemingly similarity between the two domestic measures of uncertainty (forecaster dispersion (Tankan) and rolling 1-year sales growth volatility) is interesting. Both sets of systems appear to have similar real options effects on investment. This suggests that forwards-looking and backwards-looking indicators are similarly derived, and may form the basis for interesting uncertainty measure comparison research.

Shocks simulated in the early 1990s suggests that uncertainty had a drop, rebound and overshoot impact on Japanese private fixed investment at the start of the 'Lost Decade'. Given the absence of either an obvious rebound or overshoot impact in the investment time-series, together with Horioka's 2006 finding that investment falls caused the 'Lost Decade', it seems incorrect to attribute to uncertainty shocks entire causation of a long-term recession.

9 Summary

In this paper I sought to answer three questions: Does uncertainty matter for Japanese investment? Does this impact vary over time, particularly in periods of crisis? Could uncertainty shocks have contributed to the 'Lost Decade'?

These questions generated five hypotheses: 1) uncertainty has some non-zero impact on investment, 2) an increase in uncertainty leads to a short-term fall in investment, 3) an increase in uncertainty leads to a medium-term increase in investment, 4) these impacts vary over time and 5) these impacts are greater during periods of peak uncertainty.

To consider these hypothesis I examined two classic, small-scale models of investment variously augmented with one of three uncertainty measures: a forecaster dispersion index, an implied volatility VIX index and a rolling sales growth volatility measure. Estimation of time-varying parameter VAR models with stochastic volatility indicate uncertainty has the hypothesised drop, rebound and overshoot impacts on Japanese private fixed investment. These findings are consistent with assumptions used in the large-scale modelling analysis by Bloom (2009) and Bloom et al. (2012). Contrary to expectations, such shocks appear linear in time and magnitude.

The finding that uncertainty has linear impacts on investment in Japan during the period 1990-2011 is novel to the literature, including Abel and Eberley (1999), Bloom (2009), Bachmann et al. (2013), and Caggiano et al. (2015). The TVP-VAR analysis suggests that the apparently non-linear appearance of uncertainty shocks in much of the literature may be inability to allow for stochastic volatility.

Falls in private fixed investment are linked (Horioka 2006) with Japan's 'Lost Decade', but simulated uncertainty spikes during this period consistently indicate a rebound effect inconsistent with sustained declines. Long-term collapses in investment cannot be attributed to short-term uncertainty shocks.

Areas for future investigation include potential variations in sector-level responses and causal mechanisms behind the differing apparent impacts of domestic and international, real and financial uncertainty instruments. Further, the issue of how macroeconomic policy may have variously stabilised or exacerbated investment responses to uncertainty shocks remains unclear. Extending the findings of this paper into these areas of research may assist policymakers in responding to macroeconomic crises in Japan and abroad.

10 References

References

[1] Abel, A. and Eberly, J. (1996), 'Investment and Q with Fixed Costs: An Empirical Analysis.' Manuscript. Philadelphia: Univ. Pennsylvania

[2] Ando, A. (1998), 'Demographic Dynamics and Causes of the Japanese Recession', presented at Conference of the National Bureau of Economic Research, Japan Project, Tokyo, October, 1998

[3] Bachmann, R., Elstner, S. and Sims, E (2013), 'Uncertainty and Economic Activity: Evidence from Business Survey Data', American Journal of Economics – Macroeconomics (2013), Vol. 5(2), 217-249.

[4] Barro, R.J. (2000), 'Inequality and growth in a panel of countries', Journal of Economic Growth, 5, 5-32 Bayoumi, T. (1999), 'The Morning After: Explaining the Slowdown in Japanese Growth in the 1990s,' Journal of International Economics 53, 241-259

[5] Baum, C., Caglayan, M., Stephan, A. and Talavera, O., (2008). "Uncertainty determinants of corporate liquidity," Economic Modelling, 25(5), pages 833-849

[6] Bekaert, G., Hodrick, R. and Zhang, X., (2010), 'Aggregate idiosyncratic volatility', NBER Working Paper Series No.16058

[7] Bernanke, B. (1983), 'Irreversibility, Uncertainty, and Cyclical Investment.' Quarterly Journal of Economics 98, 1, 85-106.

[8] Bernanke, B., Gertler M. and Gilchrist, S., (2000), 'The Financial Accelerator in a Quantitative Business Cycle Framework,' Handbook of Macroeconomics, North Holland.

[9] Blanchard, O. J. (1986): "Comments and Discussion," Brookings Papers on Economic Activity, 1, 153–156.

[10] Bloom, N. (2009). "The Impact of Uncertainty Shocks", Econometrica, 77/3, 623–685.

[11] Bloom, N., M. Floetotto, N. Jaimovich, Saporta-Eksten, I and Terry, S. (2012). "Really Uncertain Business Cycles", NBER Working Paper Series No.18245

[12] Bloom, N. (2012) 'The macroeconomics of uncertainty and volatility', IMF Training Seminar, February 2012

[13] Brounen, J., de Jong, A. and Koedijk, K. (2004), 'Corporate Finance in Europe: Confronting Theory with Practice', Financial Management, 33/4, 71-101

[14] Caballero, R. (1999), 'Aggregate Investment', in Handbook of Economics, (eds) Taylor, J. and Woodford, M., National Bureau of Economic Research, Cambridge, MA

[15] Caggiano, G., Castelneuvo, E. and Nodari, G, (2015), 'Uncertainty and Monetary Policy in Good and Bad Times', "Marco Fanno" working paper N.188

[16] Choi, S., (2013) 'Are the effects of Bloom's uncertainty shocks robust?', Economics Letters, Volume 119, Issue 2, May 2013, Pages 216-220

[17] Cochrane, J., (1991), 'A critique of the application of unit root tests', Journal of Economic Dynamics and Control, Volume 15, pp. 275-284

[18] Cooper, R. and Ejarque, J., (2003), 'Financial Frictions and Investment: Requiem in Q', Review of Economic Dynamics, 6, 4, 710-728

[19] Cooper, R. and Haltiwanger, J., (2006), 'On the Nature of Capital Adjustment Costs,' Review of Economic Studies, 73, 3, 611-633

[20] Corbett, J. (2012). 'Has Japan's Lost Decade(s) Changed Economic Thinking?,' The Economic Record, The Economic Society of Australia,. 88(s1), 100-105, 06.

[21] Di Mauro, F., Fornari, F. and Mannucci, D (2012), 'Stock market firm-level information and real economic activity', Working Paper, LSE

[22] Dixit, A. and Pindyck, R. (1996) 'Investment under Uncertainty', Princeton University Press

[23] Eberly, J., Rebelo, S. and Vincent, N. (2012), 'What explains the lagged-investment effect?', Journal of Monetary Economics, 59, 370–380

[24] Emerson, M. (2013), 'Cameron's big speech on Europe – No, Prime Minister!', CEPS Essays, 31/1/2013

[25] Fry, R., Hsiao, C. and Tang, C., (2011), 'Actually This Time Is Different,' CAMA Working Papers 2011-12.

[26] Hallikainen, P., Hu, Q., Frisk, E., Eikebrokk, T., Paivarinta, T. and Nurmi, A., (2006), 'The Use of Formal IT Investment Evaluation Methods in Organizations: A Survey of European Countries', Proceedings of the Twelfth Americas Conference on Information Systems, Acapulco, Mexico, August 2006

[27] Hansen, L. (2007). 'Beliefs, Doubts and Learning: Valuing Macroeconomic Risk; Richard T. Ely Lecture', American Economic Review, 97, 1-30.

[28] Hayashi, F., (1982), 'Tobin's Marginal q and Average q: A Neoclassical Interpretation,' Econometrica, 50, 1, 213-24

[29] Hayashi, F., and Prescott, E. (2002), 'The 1990s in Japan, a Lost Decade', Review of Economic Dynamics 5, 206-235

[30] Hennessey, C., Levy A., and Whited, T. (2007), 'Testing Q theory with financing frictions', Journal of Financial Economics, 83, 3, 691-717 Tnk

[31] Hong, H., Stein, J, and Yu, J., (2007), 'Simple forecasts and paradigm shifts', Journal of Finance, 57, 3, 1207-1242

[32] Hoshi, T. and Kashyap, A.K. (1990), 'Evidence on q and investment for Japanese firms', Journal of the Japanese and International Economies, 4, 4, 371–400

[33] Hoshi, T. and Kashyap, A.K. (2004), 'Japan's Financial Crisis and Economic Stagnation', Journal of Economic Perspectives, 18, 3–26.

[34] Hoshi, T., Kashyap, A. and Scharfstein, D., (1991), 'Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups,' The Quarterly Journal of Economics, 106, 1, 33-60

[35] Hubbard, R.G., (1998), 'Capital-Market Imperfections and Investment', Journal of Economic Literature , 36, 1, 193-225

[36] Jorgensen, D. (1963), 'Capital theory and investment behaviour', American Economic Review, 53 (2), 247-259

[37] Jones R. & Urasawa. S. , (2011)."Labour Market Reforms in Japan to Improve Growth and Equity, OECD Economics Department Working Papers 889, OECD Publishing.

[38] Kaplan, S., and Zingales, L. (1997), 'Do Investment-Cash Flow sensitivities provide useful measures of financing Constraints?', The Quarterly Journal of Economics, CXII-1, 169-216

[39] Kasahara H., Sawada, Y. and Suzuki, M. (2011), 'Investment and Borrowing Constraints: Evidence from Japanese Firms', presented at NBER Japan Project Meet, Tokyo, 2011

[40] Kiyotaki, N. and Moore, J. (1997), 'Credit Cycles', Journal of Political Economy, 105 (2), 211-248

[41] Kiyotaki, N. and West, K. (1996), 'Business Fixed Investment and the Recent Business Cycle in Japan', NBER Macroeconomics Annual 1996

[42] Krugman, P. (1998), 'Its baaack! Japan's slump and the return of the liquidity trap', Brookings Papers on Economic Activity, 2(2),

[43] Koo, R., (2003), 'Balance Sheet Recession: Japan's Struggle with Unchartered Economics and its Global Implications', Singapore, Wiley

[44] Lorenzoni, G., and Walentin, K., (2007). ‘Financial Frictions, Investment and Tobin’s q,’ NBER Working Papers 13092

[45] Mankiw N.G., Romer, D., and Weil, D. (1992), ‘A Contribution to the Empirics of Economic Growth’, Quarterly Journal of Economics 107(2): 407-437

[46] Motonishi, T. & Yoshikawa, H, (1999). ‘Causes of the Long Stagnation of Japan during the 1990s: Financial or Real?,’ Journal of the Japanese and International Economies, vol. 13(3), pages 181-200.

[47] Nakajima, J. (2011). "Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications" Monetary and Economic Studies, 29, 107-142

[48] Ogawa, K., and Suzuki, K, (2000). ’Uncertainty and Investment : Some Evidence from the Panel Data of Japanese Manufacturing Firms,’ Japanese Economic Review, 51, 170-192.

[49] Polk, C., and Sapienza, P (2009), ‘The Stock Market and Corporate Investment: A Test of Catering Theory’, Review of Financial Studies (2009) 22, 1, 187-217.

[50] Primiceri, G., (2005), ‘Time Varying Structural Vector Autoregressions and Monetary Policy,’ Review of Economic Studies, 72 (3), 2005, pp. 821–852.

[51] Schwert, G., (2011), ‘Stock volatility during the recent financial crisis’, European Financial Management’, 17, 5, 789-805

[52] Siebert, H., (2005), ’The German Economy: Beyond the Social Market’, Germany, Princeton University Press

[53] Shinoda, T., (2010), ’Capital Budgeting Management Practices in Japan’, Economic Journal of Hokkaido University, 39, 29-50

A Appendix

Figure 1: Time series of Japanese machinery investment (RHS, log-levels) and Tankan forecaster dispersion (LHS).

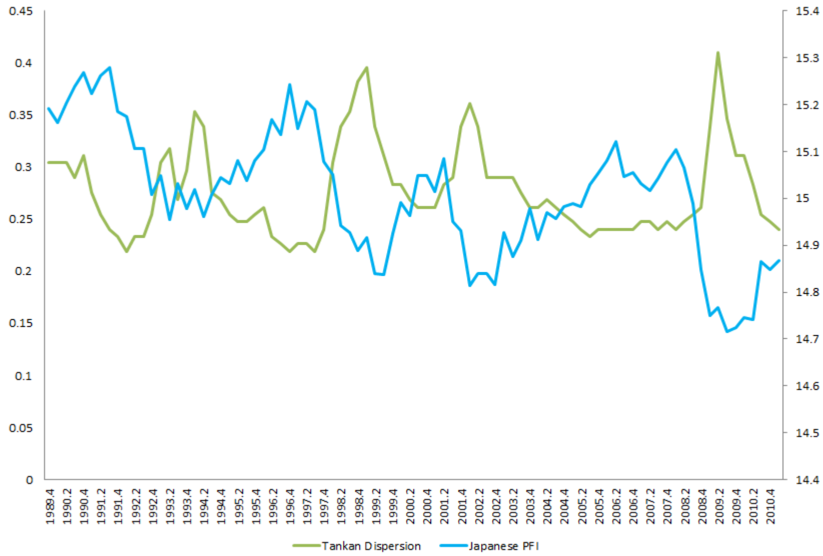


Table 1: Summary statistics of estimated variables

	MCH	K	NIKK	SALE	TANK	VIX
Mean	-0.003368	0.00112	-0.015365	0.043491	0.276354	26.74506
Median	0.001279	-0.001681	-0.002715	0.042336	0.26163	23.87
Maximum	0.122853	0.085428	0.198247	0.091101	0.410122	80.86
Minimum	-0.14234	-0.060557	-0.29062	0.015848	0.219203	12.67
Std. Dev.	0.058421	0.021425	0.099237	0.011736	0.042987	11.15403
Skewness	-0.305861	0.552069	-0.400046	0.941327	1.034364	1.777118
Kurtosis	2.64073	5.54534	2.968969	5.288178	3.509615	8.285704
Observations	85	85	85	85	85	85

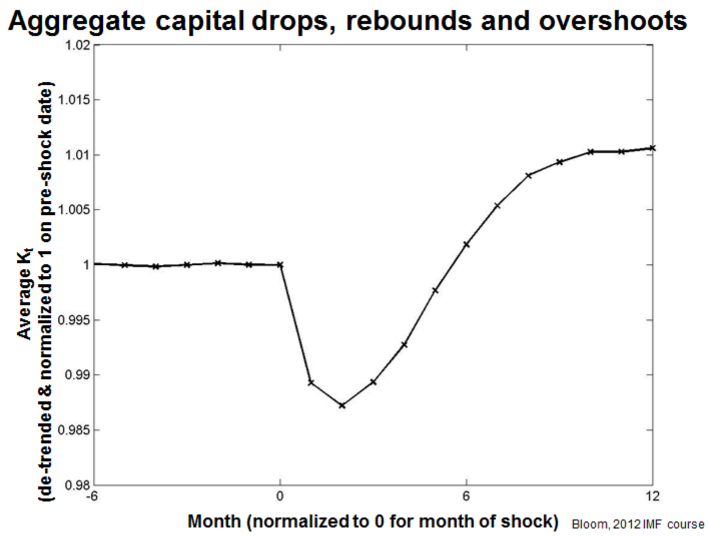


Figure 2: Canonical real options impacts of uncertainty on investment, from Bloom et al. (2012)

Table 2: Correlation and covariance statistics of estimated variables

Correlation/Covariance	MCH	K	NIKK	SALE	TANK	VIX
MCH	1					
	0.003					
K	0.196	1				
	0.000	0.000				
NKK	0.154	0.106	1			
	0.001	0.000	0.010			
SALE	0.028	-0.06	-0.036	1		
	0.000	0.000	0.000	0.000		
TANK	-0.143	-0.214	-0.052	0.283	1	
	0.000	0.000	0.000	0.000	0.002	
VIX	-0.313	-0.359	-0.386	0.233	0.378	1
	-0.201	-0.085	-0.422	0.030	0.179	122.949

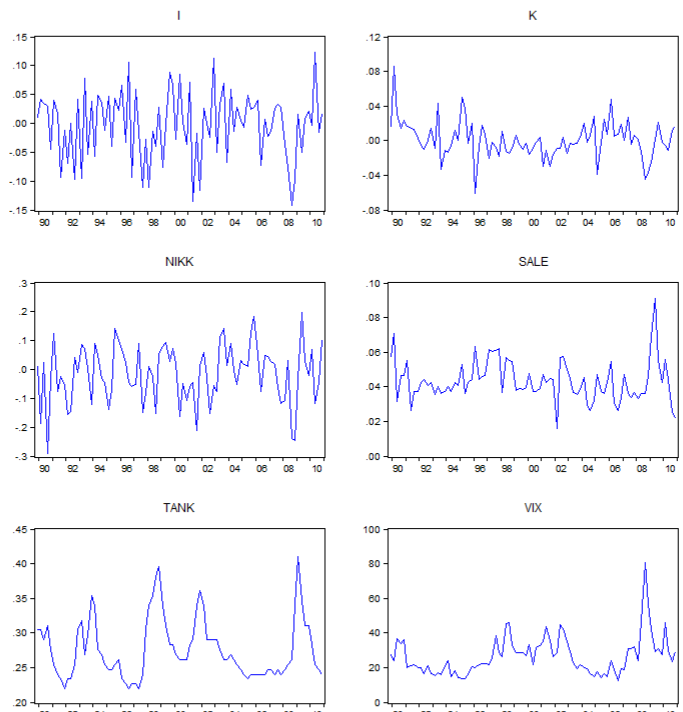


Figure 3: Time series of key variables. Investment, Capital, Nikkei 225 are first-differenced log-levels. Sale is the rolling 1-year standard deviation of Japanese non-financial company sales growth. Tankan forecaster dispersion is levels and VIX Index levels of monthly maxima.

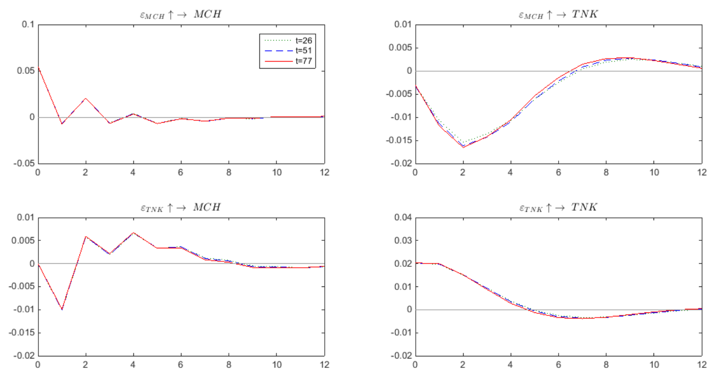


Figure 4: Impulse responses from Model 1, Tankan dispersion specification. Impulses gathered at 30%, 60% and 90% of sample period.

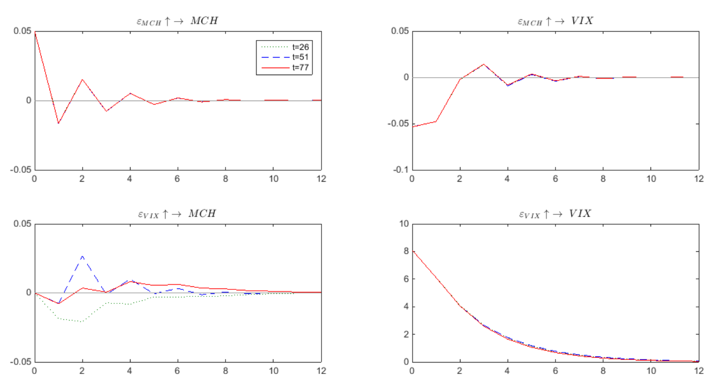


Figure 5: Impulse responses from Model 1, VIX specification. Impulses gathered at 30%, 60% and 90% of sample period.

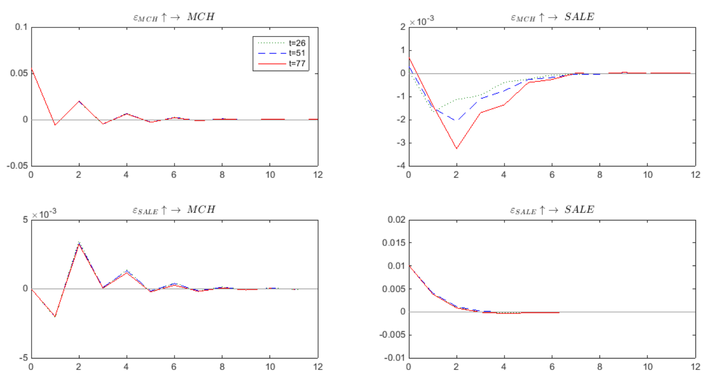


Figure 6: Impulse responses from Model 1, sales growth volatility specification. Impulses gathered at 30%, 60% and 90% of sample period.

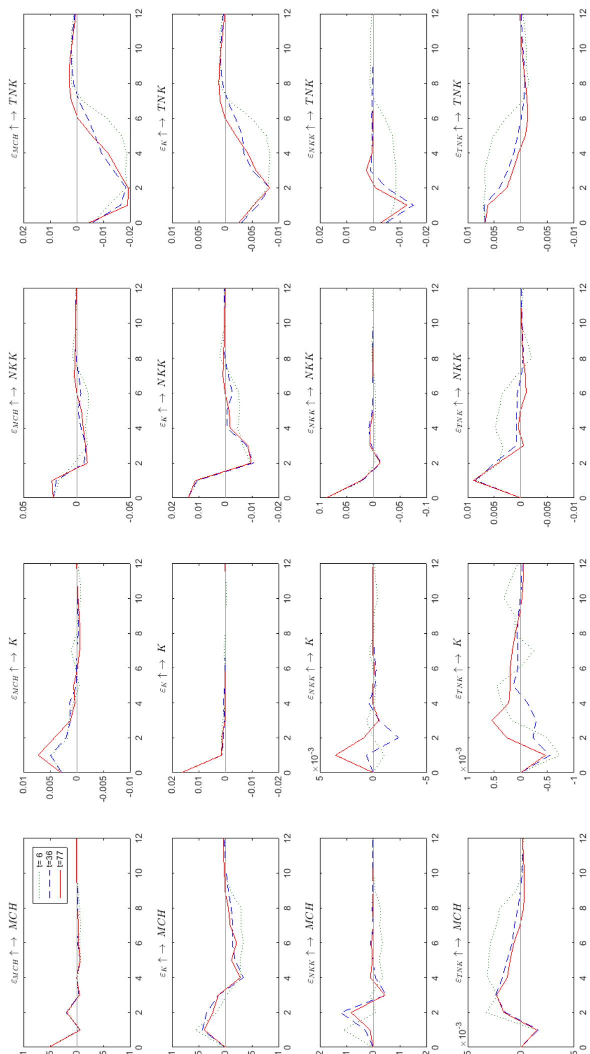


Figure 7: Impulse responses from Model 2, Tankan dispersion specification. Impulse responses gathered at periods of unusually high equity market volatility {Q4:1990, Q3:1998, Q4:2008} respectively corresponding to the lines t=6, 36, 77.

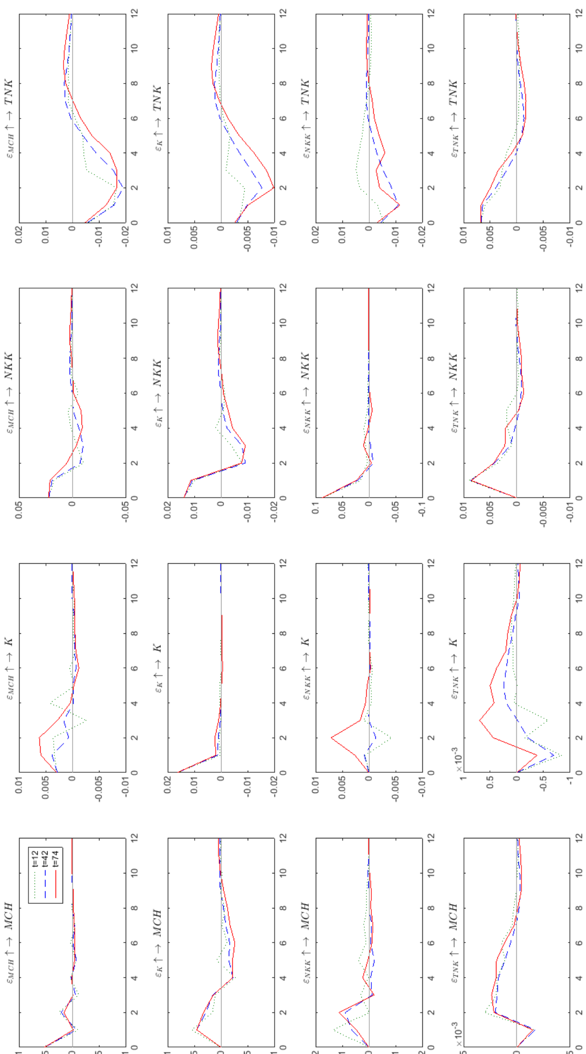


Figure 8: Impulse responses from Model 2, Tankan dispersion specification. Impulse responses gathered at periods of unusually low equity market volatility {Q2:1992, Q1:2000, Q4:2007} respectively corresponding to the lines t=12, 42, 74.

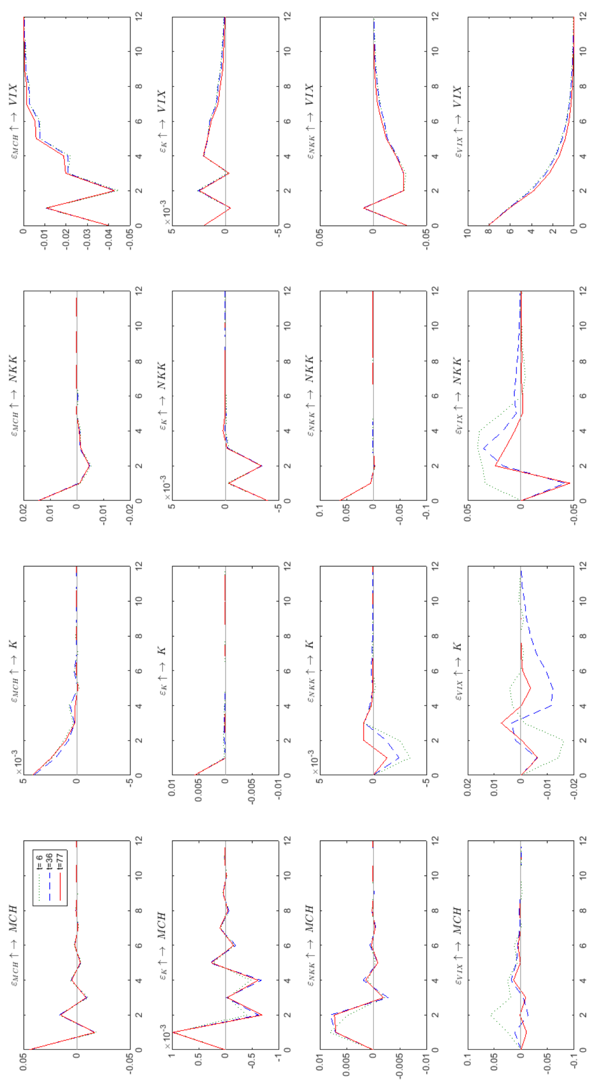
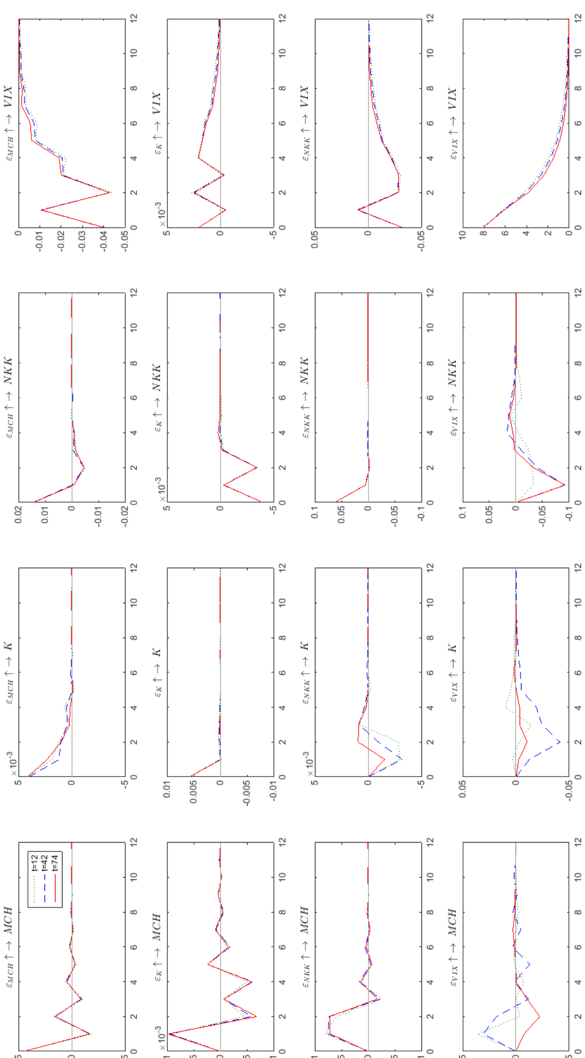


Figure 9: Impulse responses from Model 2, VIX specification. Impulse responses gathered at periods of unusually high equity market volatility {Q4:1990, Q3:1998, Q4:2008} respectively corresponding to the lines t=6, 36, 77.



εMCH ↑ → MCH
t=12
t=42
t=74
εK ↑ → MCH
εNKK ↑ → MCH
εVIX ↑ → MCH
εMCH ↑ → K
εK ↑ → K
εNKK ↑ → K
εVIX ↑ → K
εMCH ↑ → NKK
εK ↑ → NKK
εNKK ↑ → NKK
εVIX ↑ → NKK
εMCH ↑ → VIX
εK ↑ → VIX
εNKK ↑ → VIX
εVIX ↑ → VIX

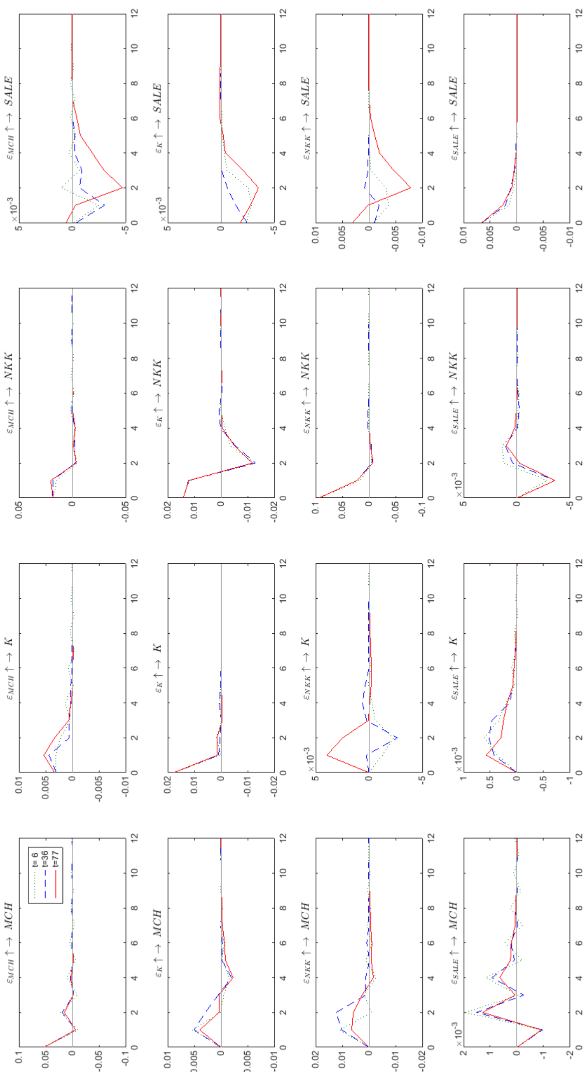


Figure 11: Impulse responses from Model 2, Sales volatility specification. Impulse responses gathered at periods of unusually high equity market volatility {Q4:1990, Q3:1998, Q4:2008} respectively corresponding to the lines t=6, 36, 77.

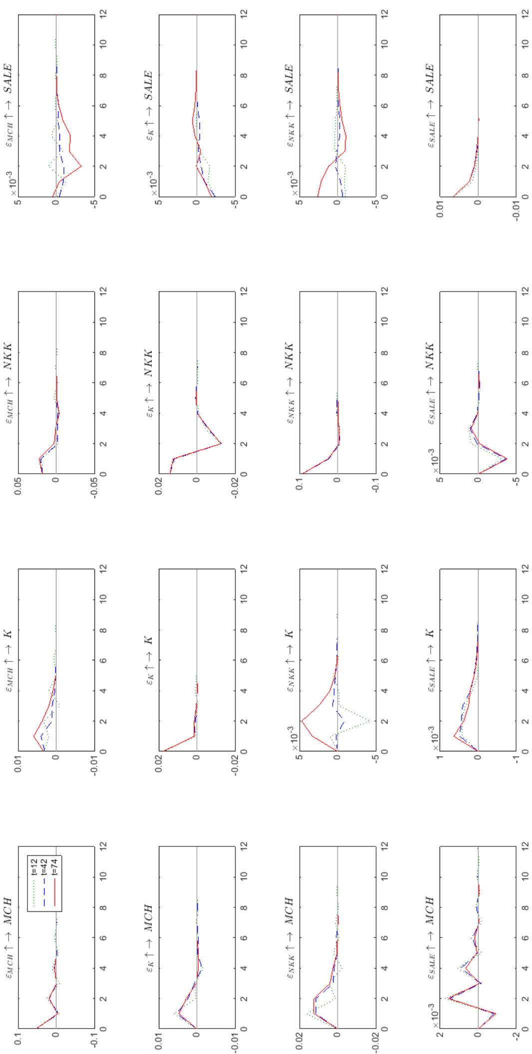


Figure 12: Impulse responses from Model 2, Sales volatility specification. Impulse responses gathered at periods of unusually low equity market volatility {Q2:1992, Q1:2000, Q4:2007} respectively corresponding to the lines t=12, 42, 74.

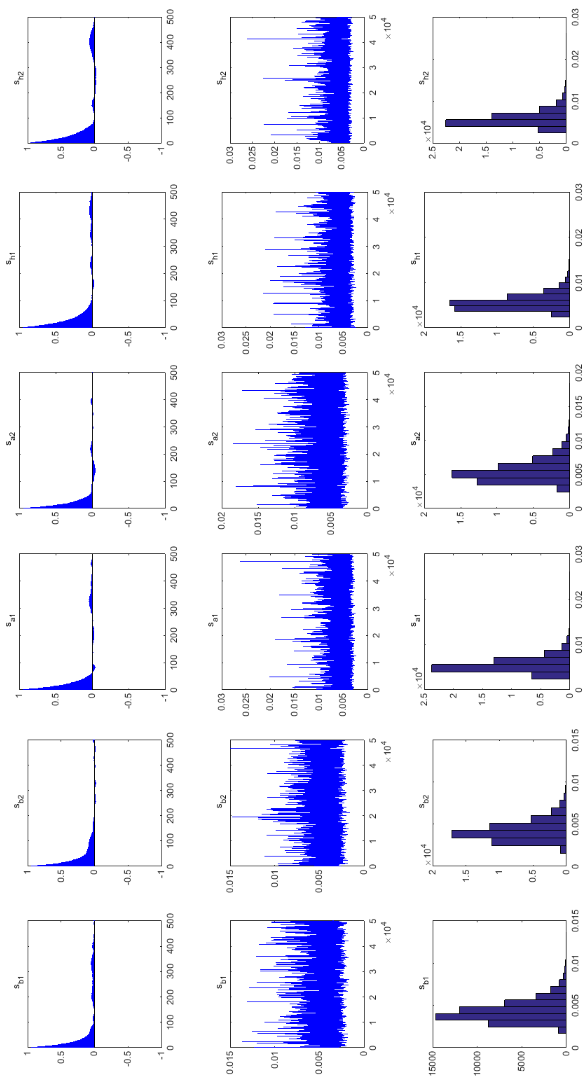


Figure 13: Parameter autocorrelation, distribution and densities from Model 2, TNK specification. All other diagnostic details available from luke.meehan@anu.edu.au