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The effect of uncertainty on output: Instruments, identification, and the role of investment ☆

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ABSTRACT

This study investigates the impact of uncertainty shocks on output in New Zealand between 1985Q2 and 2018Q4 using the Internal and External Instrument versions of the Structural Vector Autoregression model. While the existing literature has relied almost exclusively on the External Instrument approach, this method requires the invertibility of the uncertainty shock, whereas the Internal Instrument approach does not. We formally test for, and reject, invertibility in our application, reflecting that uncertainty frequently arises from concerns about future policy or economic fundamentals. As the two instrumental variable models produce quantitatively different impulse responses for output, we empirically illustrate the importance of testing for invertibility and using the results to guide model selection. We also find that the effects of uncertainty shocks on New Zealand's output are larger than previously documented — with investment a key transmission channel — suggesting that counter-cyclical policy may need to respond more aggressively to uncertainty-driven downturns.

1. Introduction

The impact of uncertainty on output is now a well-studied question in economics. Its importance as a research question has been elevated by numerous events over the last 15 years associated with heightened uncertainty: the COVID-19 pandemic, the Eurozone debt crisis, the Global Financial Crisis, and Britain's exit from the European Union to name but a few recent examples. But just how confident can we be in the empirical estimates of the effects of uncertainty on output provided in the literature? The veracity of any estimates depends on how well the uncertainty shock is identified. To make causal statements about uncertainty's effects on output, the identified uncertainty shock needs to reflect uncertainty's unanticipated movements (uncertainty's 'exogenous impulse' in the terminology of Ludvigson et al., 2021) rather than uncertainty's movements which are in response to the state of the economy. Get this identification wrong and your estimates of uncertainty's effects are likely to be wrong too.

In Structural Vector Autoregression (SVAR) models, the recursive (or Cholesky decomposition) approach to identification isolates uncertainty shocks by assuming a particular causal chain; specifically, a causal chain that precludes uncertainty and output (and other business cycle variables) both causing each other contemporaneously. Such preclusion is problematic as we have evidence for simultaneity between uncertainty and the business cycle (Ludvigson et al., 2021). Further, we know that different timing assumptions can lead to a 'wide range of results' regarding the impact of uncertainty on the economy (Baker et al., 2024, p. 2), but theory does not tell us which timing assumption is more appropriate. Despite these issues, the recursive approach to identification is the most common one employed to study uncertainty's effects on the macroeconomy using SVAR models. For example, it is the approach used in all the previous studies involving our case study country, New Zealand (see Kamber et al., 2016, Greig et al., 2018, Tran et al., 2019).

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Instrumental variable (IV) estimation has been used by various studies to examine uncertainty's impact on output (and other macroeconomic variables) without relying on the timing assumptions required of the recursive approach to identification.[1] Almost always the set up used is the External Instrument (or Proxy) SVAR, where an exogenous variable(s) instruments for the structural uncertainty shock; see Carriero et al. (2015), Piffer and Podstawski (2018), Kim (2019), Baker et al. (2023), Husted et al. (2020), Ha et al. (2022), Cieślik and Turgut (2023) and Baker et al. (2024) for papers studying uncertainty's effects using the approach.

The External Instrument approach, however, is only valid under invertibility of the shock of interest; see Stock and Watson (2018, p.919) and Plagborg-Møller and Wolf (2021, p.972). Miranda-Agrippino and Ricco (2023) note that *non*-invertibility of the shock of interest can occur in an External Instrument SVAR when there are: omitted variables, insufficient lag lengths, and anticipation and foresight about the future. The first two issues are potential threats to invertibility in most empirical applications using an External Instrument SVAR; anticipation and foresight about the future, however, seem an especially pertinent threat when uncertainty is the shock of interest. Heightened economic uncertainty, as recorded at a particular point in time, reflects uncertainty about the future economic environment or future policy in many instances. To illustrate this point, consider the time just prior to an election. At this time, particularly when there is a high chance the government will change or the election is close, uncertainty will increase as firms and households seek to form new beliefs about future government policy (Redl (2020)). Consistent with this, the US Economic Policy Uncertainty index developed by Baker et al. (2016) shows spikes upon the election of Bill Clinton, George W. Bush and Donald Trump reflecting uncertainty about what future policy or the economy under these presidents could look like.[2] When the uncertainty shock is the shock of interest, the forward-looking nature of uncertainty means invertibility is a particularly strong assumption and an assumption that needs to be tested. Our first research question is therefore: does invertibility of the uncertainty shock hold in our empirical application? Based on our answer to this first research question, we can then choose the appropriate empirical framework to answer our second research question: what impact do uncertainty shocks have on output in New Zealand? In terms of an alternative empirical framework if invertibility of the uncertainty shock does not hold, we note the Internal Instrument SVAR does not require invertibility of the shock of interest (Plagborg-Møller and Wolf, 2021).[3]

This paper sits in the empirical literature on estimating the impact of uncertainty shocks using instrumental variables and makes several important contributions to this literature. All previous studies of uncertainty using the External Instrument SVAR approach implicitly assume invertibility of the SVAR. The variation in output responses to uncertainty shocks we document across instrumental variable SVAR model formulations demonstrates for the researcher the critical importance of (i) formally testing the invertibility of the uncertainty shock and (ii) using the results of the invertibility test for selecting the appropriate model. Our second contribution is methodological: we show how narrative-based approaches, commonly used in the study of monetary and fiscal policy, can be effectively adapted to construct instruments to study uncertainty. Finally, this paper contributes to the literature on the impact of uncertainty on the New Zealand economy by presenting the first empirical estimates of the impact of uncertainty shocks that do not rely on recursive identification. The impact of an uncertainty shock on output is larger than previously estimated. Our results suggest, therefore, that policymakers wishing to run counter-cyclical policy need to respond more aggressively to uncertainty shocks than previously thought. Further, policymakers concerned about the government's fiscal position need to be aware that fiscal variables which depend on the business cycle, such as taxes and unemployment benefits, are likely to be more adversely affected by uncertainty shocks; this is to the detriment of the government's operating balance and debt.

The remainder of this paper is organised as follows. In Section 2, we discuss the construction of our instrument, and its quality; we also discuss our empirical setup. In Section 3, we discuss our estimates of the dynamic effects of uncertainty shocks on the economy. Section 4 concludes.

2. Our empirical framework and our instrument

2.1. The external instrument SVAR

Our initial empirical model is the External Instrument ('Proxy') SVAR; see Stock and Watson (2012) and Mertens and Ravn (2013). The External Instrument SVAR approach allows the classification of events used in constructing our instrument to be imperfect (i.e. contaminated by measurement error), provided they are 'not too inaccurate, on average' (Plagborg-Møller, 2022, p.1435).

Our reduced-form VAR model can be written as

$$Y_t = \alpha + \sum_{j=1}^{p} B_j Y_{t-p} + \eta_t \tag{1}$$

Y_t consists of six endogenous variables: the uncertainty index of Ryan (2025), the quarterly change in the New Zealand share price index, the output gap, the detrended inflation, the detrended nominal 90-day interest rate, and the detrended natural log of the nominal exchange rate (the Trade Weighted Index).[4]

The uncertainty index of Ryan (2025) is constructed using firm-level data from the *Quarterly Survey of Business Opinion*. Recognising that uncertainty is a latent variable, the uncertainty index of Ryan (2025) is the arithmetic average of three alternative uncertainty indices: one that equates more dispersion in firm predictions about the future with more uncertainty, one that equates larger average forecast errors by firms with more uncertainty and one that equates larger idiosyncratic forecast errors by firms with more uncertainty.[5] The construction of the uncertainty index is discussed in more detail in the Online Resource for

[1] Other alternative approaches to the recursive approach exist. Researchers can restrict the direction (sign) of the impact of uncertainty shocks on the economy (for example, see Houari, 2022, and Meinen and Roehe, 2018); as Ludvigson et al. (2021) note, this seems inappropriate given uncertainty's impact on the economy is ambiguous in theory. Brianti (2021) adopted an approach similar to sign restrictions based on the assumption that cash holdings increase following uncertainty shocks for precautionary reasons but fall following financial shocks owing to financing reasons. There have been a number of studies that have employed event-based restrictions to identify uncertainty shocks (often in combination with sign-restrictions): Ludvigson et al. (2021), Larsen (2021), Redl (2020), Caggiano et al. (2021) and De Santis and Van der Veken (2025) are examples. Other authors such as Angelini et al. (2019) use heteroskedasticity-based schemes to identify uncertainty shocks; Montiel Olea et al. (2022) note concerns about the general approach. Finally, Caldara et al. (2016), Kim et al. (2024) and Kumar et al. (2021) use a penalty function approach: judging the uncertainty shock to be the shock that leads to the largest increase in uncertainty. This approach still relies on a timing assumption but the assumption is more general than the recursive approach.

[2] The US Economic Policy Uncertainty index can be viewed here.

[3] The Internal Instrument SVAR is not assumption free, however. We will discuss these assumptions of this model later in Section 3.

[4] The share price index is sourced from OECD (2020), Share prices (indicator). doi: 10.1787/6ad82f42-en [Accessed on 15 June 2020], the inflation data are sourced from Statistics New Zealand's Infoshare, the nominal Trade Weighted Index exchange rate data and the nominal 90-day interest rate are sourced from the Reserve Bank of New Zealand [accessed 20 November 2022].

[5] Bachmann et al. (2013), Arslan et al. (2015), Girardi and Reuter (2016), Binge and Boshoff (2020) and Easaw and Grimme (2024) are other papers that use firm directional forecast errors and/or firm response dispersion to construct uncertainty measures. The rationale for averaging across the three uncertainty indices is uncertainty is a latent variable and each of our

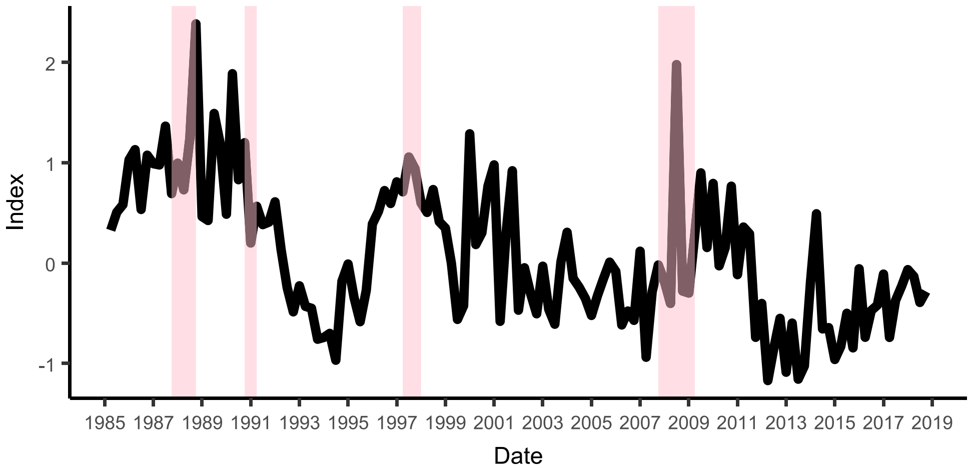


Fig. 1. Our uncertainty index.
Notes: Shaded areas are recessions as identified by Hall and McDermott (2016). The construction of the index is discussed in the Online Resource for this paper and in Ryan (2025).

this paper. Fig. 1 plots our final uncertainty measure, along with the recession dates of Hall and McDermott (2016). We see that uncertainty spikes during recessions; in particular, the Asian and Global Financial Crises. The period from mid-1980s to 1995 is also a period of high uncertainty as the New Zealand economy went under an extensive reform towards market-orientated policies (Evans et al., 1996).

The output gap is created by applying the method of Kamber et al. (2018) to the natural log of the real GDP series of Hall and McDermott (2011); inflation and the interest rate are detrended using the Hodrick–Prescott filter (lambda: 1600). We detrend the interest rate as the 1980s and early 1990s was a period of large structural change in the New Zealand economy, in particular the economy was opened up to foreign capital flows as financial markets were deregulated. This means that the equilibrium/natural interest rate has moved. We detrend inflation to take into account the introduction and changes to the inflation target. We restrict our estimation sample to 1985Q2 to 2018Q4. We start in 1985Q2 as the New Zealand dollar was floated in 1985Q1 (a significant regime shift for a small economy). We end our sample in 2018Q4 as 2018 is the last year we have the firm-level data we need to construct our uncertainty index.

To aid in our explanation of the External Instrument SVAR, we denote the structural uncertainty shock as $\epsilon_{t,U}$ and the other structural shocks as $\epsilon_{t,Y}$. We also define an impact matrix, A_0. Let A_0^U be the first column of the matrix, A_0. And let A_0^Y denote the other columns of the A_0 matrix. Using this notation means we can write the relationship between the six residuals, (η_t), in the reduced form VAR and the structural shocks as:

$$\eta_t = A_0^U \epsilon_{t,U} + A_0^Y \epsilon_{t,Y} \tag{2}$$

In the case one is looking to study a single structural shock, as we are, invertibility requires $A_0^{U\prime}\eta_t = \epsilon_{t,U}$. This is equivalent to assuming the structural shock of interest — the uncertainty shock, in our case — can be recovered from current and past values of the observable variables (Plagborg-Møller and Wolf, 2021, equation 12); this is why anticipation or forward-looking behaviour represents a threat to invertibility. Finally, we note the reduced form variance–covariance matrix, $\sum_{\eta\eta}$, can be defined as: $\sum_{\eta\eta} = E(\eta\eta') = A_0 \sum_{\epsilon\epsilon} A_0'$, where $\sum_{\epsilon\epsilon} = E(\epsilon\epsilon')$

We require the instrument, m_t, to met three conditions:

I. $E[\epsilon_{t,U} m_t] \neq 0 = \kappa$ (the relevance condition)
II. $E[\epsilon_{t,Y} m_t] = 0$ (the exogeneity condition)
III. $\sum_{\epsilon\epsilon} = \text{D} = \text{diag}(\sigma_{\epsilon_{t,U}}, \ldots, \sigma_{\epsilon_{t,TWI}})$ which implies $\sum_{\eta\eta} = A_0 D A_0'$ (the condition that the structural shocks are uncorrelated)

If we multiply equation (2) by the instrument and take the expectation, we get:

$$E(\eta_t m_t) = E[(A_0^U \epsilon_{t,U} + A_0^Y \epsilon_{t,Y}) m_t] \tag{3}$$

which can be rewritten as:

$$E(\eta_t m_t) = A_0^U E(\epsilon_{t,U} m_t) + A_0^Y E(\epsilon_{t,Y} m_t) \tag{4}$$

Condition (II) above — the exogeneity condition — implies that the second term in the above equation is zero, so we can state:

$$\gamma = E(\eta_t, m_t) = A_0^U \kappa \tag{5}$$

That is, the covariance between the reduced-form residuals and the instrument identifies A_0^U up to scale and sign. Montiel Olea et al. (2022, equations 2.7-2.9) show that this sufficient to calculate structural impulse responses with respect to $\epsilon_{t,U}$.[6]

2.2. Our instrument: construction

The general approach to creating instruments in the uncertainty literature has generally had two steps: (1) identify a set of uncertainty events (months or quarters with high uncertainty) and (2) measure the unexpected change in uncertainty. Step one — identifying a set of uncertainty events — has been done a number of ways. One approach is looking for months/ quarters where an uncertainty index peaks. Bloom (2009) isolates uncertainty events by looking at the months in which the CBOE S&P Volatility Index (VXO) peaks and then assigns a month a value of one if it contains a VXO peak and zero otherwise; Bloom (2009) identifies a peak as when the (detrended) VXO is 1.65 standard deviations above the mean of the detrended series. Carriero et al. (2015) use this variable as an instrument in their External Instrument SVAR. A second approach to identifying uncertainty events is to use

uncertainty indices is likely to be subject to measurement error. The hope is by averaging the three indices that any idiosyncratic noise in any one measure is removed. Among others, Binge and Boshoff (2020) and the Working paper version of Baker et al. (2016), Baker et al. (2015) (and the associated website), adopt this approach to combining uncertainty indices constructed using different methods. The Supplementary Materials of Ryan (2025) shows that our uncertainty index is reasonably well correlated with other measures of uncertainty created for New Zealand using different methodologies.

[6] A scale normalisation, $A_{0,1}^U = 1$ so that $\gamma_{1,1} = E(\eta_t, Z_t) = \kappa$, is also needed.

Google trends data. Ha et al. (2022) identify dates where tensions on the Korean Peninsula were escalating and de-escalating based on the prevalence of certain Google search terms; they equate escalation and de-escalation (as revealed by search behaviour) with high and low uncertainty periods. A final approach to identifying uncertainty events is the approach of Baker et al. (2024). Baker et al. (2024) look for 'disaster' events in numerous countries: events that have had a significant effect on deaths or GDP, or resulted in political regime change. Piffer and Podstawski (2018) adopt a hybrid approach taking uncertainty index peaks (like Bloom, 2009) and augmenting them with disaster events (like Baker et al., 2024)—the hybrid approach is the approach we adopt.

To identify uncertainty peaks, we follow Bloom (2009). We identify uncertainty peaks as quarters where the uncertainty series is 1.65 standard deviations above its trend value.[7] The trend value is estimated using the Hodrick–Prescott filter. We identify uncertainty peaks as quarters where there are significant departures in the uncertainty series from its trend value to account for structural change in the New Zealand economy. Our uncertainty measure is highly elevated through the 1980s and early 1990s when the New Zealand economy went through a significant structural reform (see Evans et al. (1996) for a discussion of the reforms and Fig. 1 for a plot of the uncertainty measure). If we did not work with deviations from trend (and worked with deviations from the mean of the series, say), we would get a high concentration of uncertainty peaks in this early part of the sample period when the reform occurred and few later. A fair criticism would then be that the effects of the uncertainty shock on output we estimate are 'local' to this period of economic reform and therefore not relevant to the New Zealand economy post the economic reform.

Our initial procedure identifies ten quarters as uncertainty peaks; see the second column of Table 1.[8] We add four quarters when natural disasters occurred (see the third column of Table 1): (1) 1987Q1: the Edgecombe earthquake; (2) 2010Q3: the first Christchurch earthquake (3) 2011Q1: the second Christchurch earthquake and (4) 2016Q4: the Kaikoura Earthquake. These earthquakes were chosen owing to their scale and significance. The Edgecombe earthquake affected various towns and cities in the upper North Island. The Christchurch earthquakes affected a large population centre. The Kaikoura earthquake cut off a key transport link.

Regarding the quarters identified as either uncertainty peaks or significant natural disasters, we cannot simply just assume that the uncertainty in these quarters is exogenous to other structural shocks in the model. Piffer and Podstawski (2018) note, by just using the peaks in his uncertainty index, Bloom (2009) (and thus Carriero et al., 2015) implicitly assumes that a high uncertainty value is due to exogenous causes; this is not necessarily true. To establish exogeneity, Piffer and Podstawski (2018) use the variations in the price of gold around the identified uncertainty events to measure the unexpected change in uncertainty. In a similar vein, Ha et al. (2022) construct several instrumental variables based on high-frequency changes in asset prices and exchange rates around their event dates. We refrain from using changes in asset prices and/or exchange rates as New Zealand is a classic (very) small open economy, and its financial prices and exchange rates move not just owing to domestic developments but also international ones.[9] Rather, we use evidence from newspapers and official documents to classify whether the uncertainty associated with the event represents exogenous variation in uncertainty, or whether the uncertainty associated with the event is coming from the business cycle or financial markets (that is, correlated with other structural shocks in the model). There is a tradition of using narratives in other areas of macroeconomics to isolate unexpected/exogenous movements in variables. Romer and Romer (2010), for example, use budget documents and speeches to isolate exogenous changes in tax motivated by ideology or reducing inherited deficits from endogenous changes in tax reflecting the state of the U.S. economy; Romer and Romer (1989), and subsequent papers by the same authors, use Federal Reserve documents to classify the Federal Reserve's monetary policy actions as those motivated by affecting output and those that are not.

Table 1
Peaks and natural disasters considered in instrument construction.

Quarter	Peak in uncertainty series	Disaster	Included?
1987Q1		Edgecombe EQ	Included
1988Q4	x		Included
1990Q2	x		Included
2000Q1	x		Included
2001Q1	x		No
2001Q4	x		No
2008Q3	x		No
2009Q3	x		Included
2010Q1	x		No
2010Q3		First Christchurch EQ	No
2010Q4	x		No
2011Q1		Second Christchurch EQ	No
2014Q2	x		Included
2016Q4		Kaikoura EQ	Included

Notes: EQ is short for earthquake; uncertainty peaks are quarters where the uncertainty series is 1.65 standard deviations above its trend value. The *Included?* column indicates whether the quarter is included in the final instrument list.

Examining the narrative record, as set out in historical newspapers and official documents, we exclude five uncertainty peaks and two natural disasters from our event list as we feel that a substantial part of the uncertainty in the quarter might reflect the state of the business cycle. The excluded quarters are: (1) 2001Q1 and 2001Q4 as the US economy (and therefore the world economy) was adversely affected by the bursting of the dot-com bubble and then the September 11 attacks; (2) 2008Q3, as September 2008 saw the second and more intense wave of the GFC emerge as Lehman Brothers was allowed to collapse and (3) 2010Q1, 2010Q4 and 2011Q1, as financial markets were affected by the Eurozone crisis and the US debt ceiling crisis. Dropping these quarters from our list, leaves us with seven quarters (see the final column of Table 1). We provide more evidence for inclusion of quarters in, and exclusion of quarters from, our instrument list in the Online Resource. With regard to 1990Q2 and 2009Q3, we note for the External Instrument SVAR it is only a requirement that the instrument is exogenous to contemporaneous macroeconomic and financial shocks. The quarter 1990Q2 predates the so-called Gulf war recession, while 2009Q3 is sandwiched in between the initial shocks that started and propagated the GFC in 2007 and 2008, and the Eurozone crisis, which originated in 2009Q4. Our instrument consists of allocating that quarter's value of the uncertainty index to the seven quarters marked 'Included' in Table 1; all other quarters have a value zero.

[7] There is a slight difference between our approach and the approach of Bloom (2009). Bloom (2009) detrends the uncertainty series first and identifies a peak as when the detrended uncertainty series is 1.65 standard deviations above the mean of the detrended uncertainty series.

[8] Because we identify uncertainty peaks as quarters where the uncertainty series is 1.65 standard deviations above its trend value (and as this is a one-sided test), we are classifying uncertainty peaks as quarters where the value of the uncertainty index is different from the trend value at a 95 percent level of statistical significance. In the Online Resource for this paper, we explore the sensitivity of the identified uncertainty peaks to alternative thresholds for inclusion. We also explore the sensitivity of our key result — the estimated impact on uncertainty on the output gap — when the model is run using instruments constructed using different thresholds. The estimates of the impact on uncertainty on the output gap are similar under alternative thresholds.

[9] Suggestive evidence for this claim is that McDonald (2012) finds international drivers are much more significant at explaining the forecast errors in the real exchange rate than domestic factors at all the forecast horizons he examines.

2.3. Our instrument: Exogeneity and relevance

The instrument exogeneity condition, condition (I), is that our instrument is contemporaneously uncorrelated with the other structural shocks in the model. This assumption is not directly testable as the true structural shocks are unobserved. However, as other papers do — Piffer and Podstawski (2018) and Ha et al. (2022), for example — we can conduct some tests for instrument exogeneity by regressing our instrument on some structural shock series (or proxies) from various sources:

$$\zeta_{t,i} = \beta_1 + \beta_2 m_t + \xi_t \quad (6)$$

where m_t is our instrument and $\zeta_{t,i}$ is the structural shock series i of interest.

Piffer and Podstawski (2018) test the exogeneity of their instruments by regressing them against identified oil, monetary, and fiscal policy shocks as well as financial and news shocks from other studies. Such shock series are difficult to source for New Zealand for the whole period of our study, so we make use of the shock series we can source. We have some estimates of fiscal and monetary policy shocks from Ryan and Holmes (2024). This paper identifies government spending and net tax shocks using the Blanchard and Perotti (2002) method and, in one specification, 90-day interest rates are included in the model so monetary policy shocks can be identified. Table 2 shows that there are no statistically significant correlations between the net tax, government spending and monetary policy shocks from the model of Ryan and Holmes (2024) and our instrument, when significance is assessed at either the 5 or the 10 percent level. In Table 2 we also see our instrument is not correlated with the oil supply and consumption shocks of Baumeister and Hamilton (2019).[10] The results in Table 2 also suggest that we cannot reject the null hypothesis of no correlation between our instrument and shocks to global economic activity.

Piffer and Podstawski (2018) find their instrument is correlated with news events and therefore have to modify their empirical set up to allow for this. We test our instrument against the news shocks from the baseline, three variable model of Beaudry and Portier (2014),[11] as well as the news shocks from Barsky and Sims (2011) model. Our instrument appears exogenous to these news shocks. We note that the news shocks we use are estimated using U.S. data, and so are not New Zealand specific (although overseas events impact significantly on the New Zealand economy). To test for a correlation between the instrument and New Zealand news, we regress the instrument on the change in the net respondees to the *Quarterly Survey of Business Opinion* who think the economic outlook will improve—we think any positive or negative news about the economy will be reflected in this variable. We find no statistically significant correlation.

Our final test relates to foreign uncertainty. We use three measures of US uncertainty from Jurado et al. (2015): Financial, real activity and macro uncertainty.[12] Our instrument appears uncorrelated with all these series.[13] Taken together, the results reported in Table 2 give us a degree of confidence in the exogeneity of our instrument to other structural shocks in the model.

Finally, we test condition II — instrument relevance — following Montiel Olea et al. (2021), via the heteroskedasticity-robust first-stage F statistic. Our first-stage regression is our New Zealand uncertainty index on our instrument and five lags of the New Zealand uncertainty index. The F-statistic, based on the Wald test, for our instrument is 70.6; this number is greater than 10 which Montiel Olea et al. (2021) state is the rule of thumb cut off for weak instruments.[14]

3. Results

3.1. External instrument SVAR results

Fig. 2 plots the impulse responses for a one-unit (which is also a one standard deviation) shock to our uncertainty index (the solid line), where the shocks are identified via the instrument using the External Instrument SVAR. We show two (90%) confidence sets, both calculated following Montiel Olea et al. (2021). The first is the delta-method confidence set (area bounded by the black dotted lines) with heteroskedasticity-robust standard errors, and the second is the weak-instrument-robust confidence set (the shaded area).[15] Montiel Olea et al. (2021) note that the weak-instrument-robust confidence set being wider than the delta-method confidence set provides evidence of a weak instrument. Fig. 2 shows we do not generally observe this for our instrument, indicating that it is not weak and thereby confirming our assessment in Section 2.3.

Fig. 2 shows uncertainty shocks have a large negative impact on output. The fall in output is consistent with declines both in investment (as firms delay irreversible investment) and in consumption (as household delay nondurable consumption). Owing to the prospect of falling demand in the economy, the profit outlook for firms worsens and share prices fall. The peak negative impact on the output gap is 0.59 percentage points (in the fourth quarter post the uncertainty shock), and four percentage points on share prices (in the quarter when the uncertainty shock occurs). The delay in the uncertainty shock affecting output reflects that existing investment projects cannot just be discontinued straight away.

Shifting to the nominal exchange rate, consistent with Kamber et al. (2016) and Ryan (2025) we see the exchange rate depreciate. Unlike the US dollar, the NZ dollar is not viewed as a safe-haven currency and thus tends to depreciate in times of uncertainty. A depreciating exchange rate is also consistent with the role of shock absorber the New Zealand currency plays; see Karagedikli et al. (2016).

We also see nominal (90-day) interest rates fall, after an initial increase. The eventual decline in interest rates appears consistent with monetary policy being loosened as the economy weakens owing to the uncertainty shock. The initial increase in the interest rate is somewhat unexpected. We will return to this result, and the inflation result (which is key to understanding the interest rate result), in Section 3.5.

3.2. Internal instrument SVAR results

A requirement of the External Instrument SVAR is the shock of interest is partly invertible (see Eq. (4)). Invertibility of uncertainty shock is the requirement that the structural uncertainty shock can be recovered from current and lagged values of the observed data. This rules out the uncertainty shock reflecting anticipation about future events—for example, concerns about future economic policy or economic fundamentals. As we noted in the Introduction, we feel this is a strong assumption and an assumption that needs to be tested.

Plagborg-Møller and Wolf (2022) propose a formal test of invertibility of shocks. Invertibility holds if $R_0^2 = 1$, where R_0^2 is the R squared

[10] The shocks of Baumeister and Hamilton (2019) are monthly. We take the mean of the shock over the relevant quarter to transform the monthly series into a quarterly frequency.

[11] This is the Beaudry and Portier (2014) model where consumption is the third variable.

[12] We averaged the monthly series from Jurado et al. (2015) over the relevant quarter to create a quarterly series.

[13] One could make the argument that the instrument need not be uncorrelated with foreign uncertainty. A foreign event that causes an exogenous impulse for foreign uncertainty also represents an exogenous impulse for New Zealand uncertainty. But these foreign events might affect growth in New Zealand's trading partners and New Zealand's exchange and interest rates via other channels thereby confounding the estimates of domestic uncertainty on the New Zealand economy.

[14] The restricted model is the regression of our New Zealand uncertainty index on its five lags.

[15] Based on 10,000 bootstrap replications.

Table 2
Statistics assessing the exogeneity of the instrument.

	β_1	*P*-value	Estimation period
	Shocks from Ryan and Holmes (2024)		
Government spending	0.19	0.98	1985Q2–2017Q4
Net Tax	2.78	0.11	1985Q2–2017Q4
Monetary Policy	0.43	0.28	1985Q2–2017Q4
Output	0.14	0.31	1985Q2–2017Q4
	Shocks from Baumeister and Hamilton (2019)		
Economic activity	0.05	0.27	1985Q2–2018Q4
Oil supply	0.21	0.54	1985Q2–2018Q4
Oil consumption	−0.47	0.43	1985Q2–2018Q4
	News shocks		
Barsky and Sims (2011)	0.04	0.89	1985Q2–2007Q3
Beaudry and Portier (2014)	0.18	0.36	1985Q2–2012Q3
Change in the economic outlook	0.45	0.92	1985Q2–2018Q4
	Foreign uncertainty indices		
Real activity uncertainty from Jurado et al. (2015)	0.01	0.51	1985Q2–2018Q4
Financial uncertainty from Jurado et al. (2015)	0.04	0.36	1985Q2–2018Q4
Macro uncertainty from Jurado et al. (2015)	0.02	0.20	1985Q2–2018Q4

Notes: P-values are based on the heteroskedasticity-robust standard errors for the estimate of β_1.

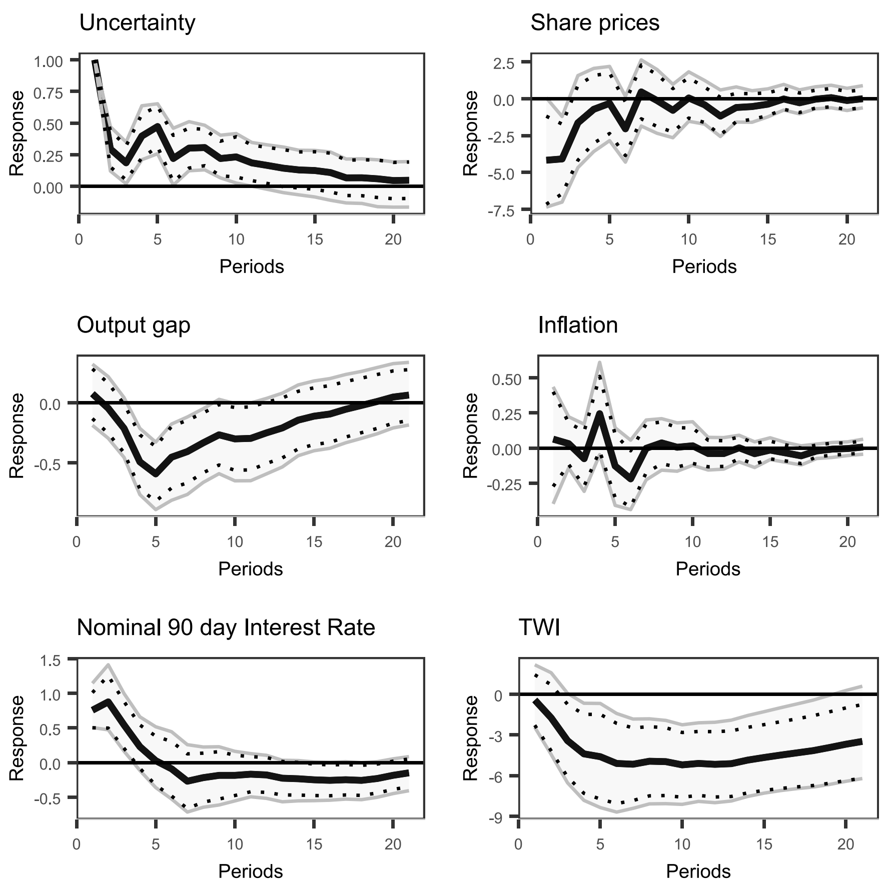


Fig. 2. Responses of the variables to a one-unit shock to uncertainty: External Instrument SVAR.
Notes: Impulse responses from the External Instrument SVAR are the solid lines. Shaded areas are the 90% weak-instrument-robust confidence sets. The areas enclosed by the dotted lines are the 90% delta-method confidence sets. The units of the responses are all percentage points, except the TWI which is percent and uncertainty which is index units. *TWI* stands for Trade Weighted Exchange Rate.

value if one could regress the true uncertainty shock series on the lags and contemporaneous values of the other variables in the model. A weaker requirement, recoverability, holds if $R^2_\infty = 1$. In this case, R^2_∞ is the R squared value from regressing the true uncertainty shock series on lags and leads of the other variables in the model (and their contemporaneous values).

As the true uncertainty shock is unknown, (a transformed version of) the instrument is used as a proxy. Equation (17) of Plagborg-Møller and Wolf (2022) states we can estimate the bounds for the population value of R^2_l (where l is either 0 or ∞) as

$$R^2_l = [\frac{1}{\hat{\alpha}^2_P} \times Var(E(\tilde{m}_t|\{Y_\tau\}_{\infty<\tau<t+l})), \frac{1}{\hat{\alpha}^2_Q} \times Var(E(\tilde{m}_t|\{Y_\tau\}_{\infty<\tau<t+l}))] \quad (7)$$

$\tilde{m}_t$ are the residuals from the regression of the instrument, m_t, on lagged values of itself, as well as the other variables in the model (Y_τ). Examination of Eq. (7) reveals that the bounds of the R^2_l depend on two estimates of a scalar α^2: $\hat{\alpha}^2_P$ and $\hat{\alpha}^2_Q$. α^2 is the amount of variation in the true structural uncertainty shock that is accounted for by the

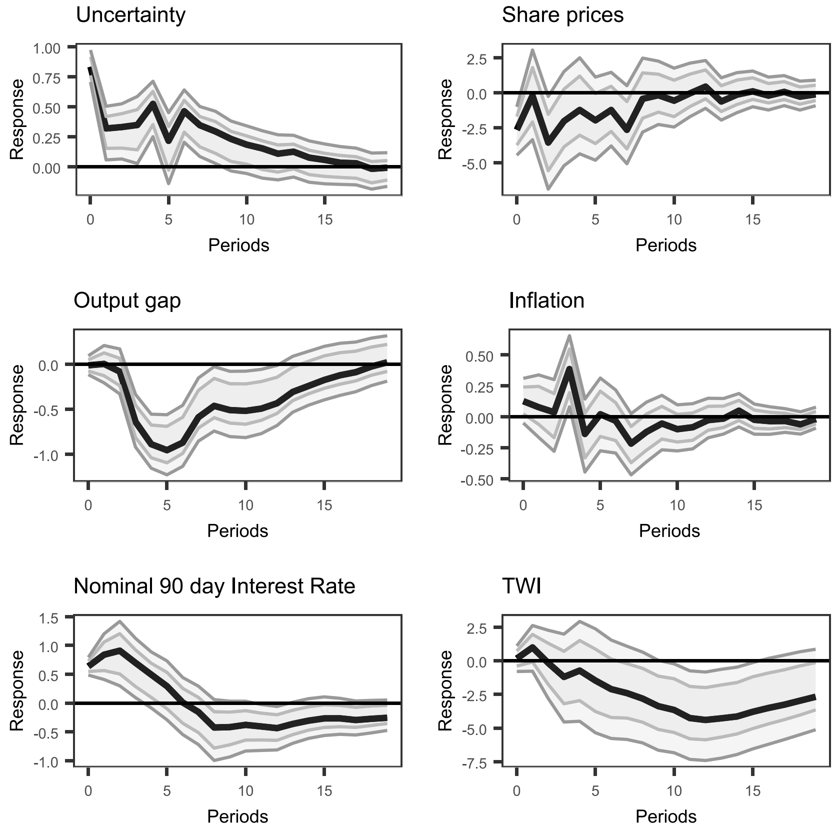


Fig. 3. Responses of the variables to a one-unit shock to uncertainty: Internal Instrument SVAR.
Notes: The dark grey and light grey areas represent 68% and 90% confidence intervals based on a wild bootstrap using 10,000 replications. The units of the responses are all percentage points, except the TWI which is percent and uncertainty which is index units. *TWI* stands for Trade Weighted Exchange Rate. The impulse responses to the uncertainty shock are derived via the Cholesky decomposition of $\sum_{\tilde{\eta}\tilde{\eta}} = E[\tilde{\eta}_t \tilde{\eta}_t']$, where $\tilde{\eta}_t$ are the reduced form residuals from a VAR estimated on a dataset consisting of the instrument (ordered first) and then the uncertainty index, the change in the share price, the output gap, inflation, the interest rate and the exchange rate (TWI).

Table 3
Test statistics for invertibility and recoverability.

Test	Bound estimates	90 per cent confidence interval
Invertibility (R_0^2)	[0.29, 0.70]	[0.18 , 0.83]
Recoverability (R_∞^2)	[0.41, 1]	[0.31, 1]

Notes: The bounds estimates are calculated using Eq. (7) in the text.

instrument. $\hat{\alpha}_P^2$, estimated by $\widehat{\text{Var}}(\tilde{m}_t)$, would be closer to the true value of α^2 if we had a perfect instrument for the uncertainty shock. $\hat{\alpha}_Q^2$, estimated by $\widehat{\text{Var}}(E(\tilde{m}_t|\{Y_\tau\}_{-\infty<t<\infty}))$, would be the closer to the true value of α^2 if the uncertainty shock is invertible.[16]

Table 3 shows our estimated bounds and 90 percent confidence intervals for R_0^2 and R_∞^2. As the confidence interval for R_0^2 does not contain one, we reject invertibility. This means the structural uncertainty shock cannot be recovered from the current and lagged values of the observed data. This assumption is required for the External Instrument SVAR, so its violation invalidates the model's use. As the confidence interval for R_∞^2 does contain one, we do not reject recoverability. Recoverability is required for being able to estimate the contribution of uncertainty shocks to the business cycle (see Section 3.7).

When the shock of interest is not invertible. Plagborg-Møller and Wolf (2021, p.975) recommend the 'Internal Instrument approach' for estimating the structural impulse responses. Under this approach, the instrument (m_t) is ordered first in a recursive SVAR with the original variables (Y_t).[17] Defining $\tilde{Y}_t = [m_t, Y_t]$, the VAR becomes $\tilde{Y}_t = \alpha + \sum_{j=1}^{p} B_j \tilde{Y}_{t-p} + \tilde{\eta}_t$. The impulse responses to the shock of interest, the uncertainty shock in our case, can be derived up to scale by the Cholesky decomposition of $\sum_{\tilde{\eta}\tilde{\eta}} = E[\tilde{\eta}_t \tilde{\eta}_t']$; see Jordà and Mertens (2022).[18]

As we reject the invertibility of the uncertainty shock, we reestimated our model using the Internal Instrument approach. Owing to concerns about the model's lack of invertibility, this is our preferred model of the two.[19] It should be noted that the Internal Instrument

[16] The reader is referred to Section 4 of Plagborg-Møller and Wolf (2022) for further information.

[17] Y_t consists of the uncertainty index, the quarterly change in the New Zealand share price, the output gap, inflation, the interest rate and the exchange rate (TWI).

[18] It is worth reflecting on the differences between the Internal Instrument SVAR, where the instrument is ordered first, and the more usual approach with no instrument and the uncertainty index ordered first. Both models are identified by recursive (Cholesky decomposition) identification, which assumes that there are no linear combinations of the other structural shocks in the model involved in determining the first uncertainty shock in both models; see Bruns and Lütkepohl (2025). This assumption is more plausible in the Internal Instruments SVAR where the uncertainty instrument has been constructed to be contemporaneously independent of other structural shocks in the model; whereas in the standard (non-instrumented) recursive SVAR model it is harder to defend this assumption, especially when Fig. 1 shows the uncertainty index spikes during economic downturns.

[19] Plagborg-Møller and Wolf (2021, p. 973–974) note the similarity between the Internal Instrument approach and the well-known local projection approach; specifically, the two approaches produce identical impulse responses at

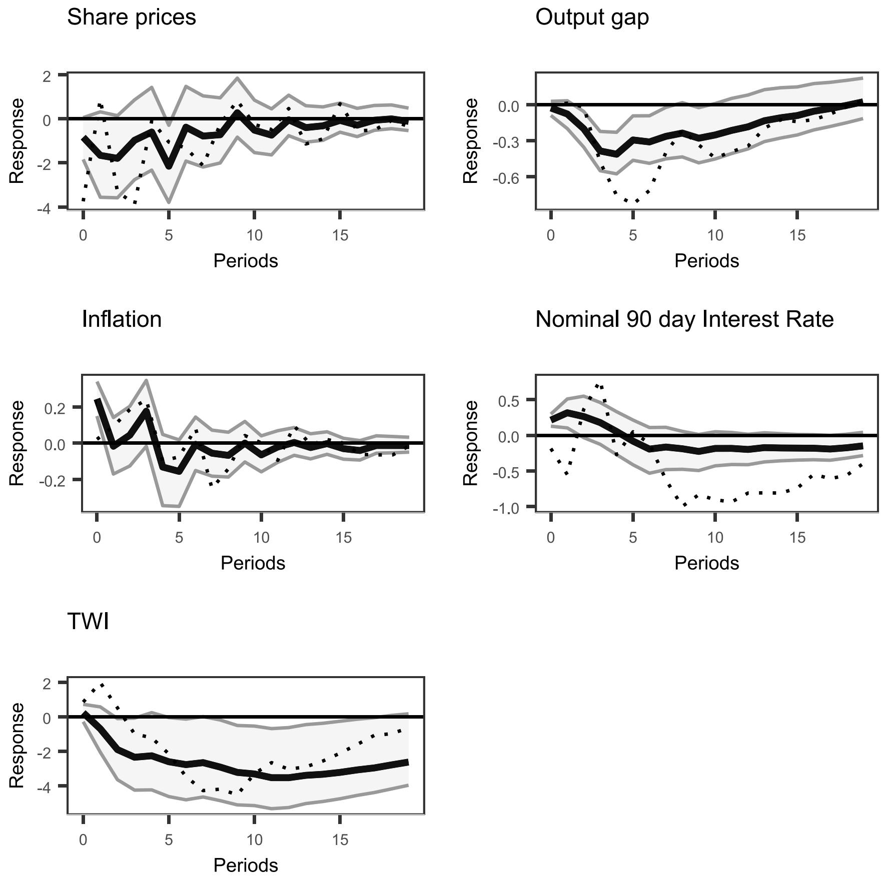


Fig. 4. Responses of the variables to a one-unit shock to uncertainty: Comparison of the Internal Instrument and non-instrumented SVARs.
Notes: Impulse responses from the non-instrumented recursively-identified SVAR are the solid lines and the shaded areas are the associated 90 per cent confidence intervals. Impulse responses from the Internal Instrument SVAR are the dotted lines. The units of the responses are all percentage points, except the TWI which is percent and uncertainty which is index units. *TWI* stands for Trade Weighted Exchange Rate. The non-instrumented SVAR impulse responses to the uncertainty shock are derived via the Cholesky decomposition of $\sum_{\eta\eta} = E[\eta_t \eta_t']$, where η_t are the reduced form residuals from a VAR estimated on a dataset of the uncertainty index (ordered first), the change in the share price, the output gap, inflation, the interest rate and the exchange rate (TWI). The Internal Instrument impulse responses to the uncertainty shock are derived via the Cholesky decomposition of $\sum_{\tilde{\eta}\tilde{\eta}} = E[\tilde{\eta}_t \tilde{\eta}_t']$, where $\tilde{\eta}_t$ are the reduced form residuals from a VAR estimated on a dataset of the instrument (ordered first) and then the uncertainty index, the change in the share price, the output gap, inflation, the interest rate and the exchange rate (TWI).

SVAR is not assumption free. The Internal Instrument SVAR requires the instrument only be correlated with lagged shocks through observed lagged variables; the External Instrument SVAR does not require this (Plagborg-Møller and Wolf, 2021, p.973, footnote 33). To satisfy this assumption, it is helpful for a model to have a large set of variables, such as we have. A second requirement of the Internal Instrument SVAR is lead exogeneity of the instrument. One perhaps might be concerned that including 1990Q2 (which was followed by the so-called Gulf war recession), and including 2009Q3 (which was followed by the Euro crisis) might mean our instrument does not meet this assumption with respect to economic activity shocks. In the Online Resource to this paper, however, we provide evidence that lead exogeneity with respect to economic activity shocks appears to hold. Further, in one of our sensitivity tests (reported in Section 3.6) we show our results are robust to dropping these quarters as uncertainty events used in the construction of our instrument.

Fig. 3 shows the impulse responses estimated with the Internal Instrument SVAR.[20] The impulse responses for all variables are broadly similar to the External Instrument SVAR, but there is one important difference: the impulse response for the output gap shows uncertainty has a much larger negative impact on the output gap in the Internal Instrument SVAR model. Specifically, the peak impact on the output gap is larger: a 0.96 percentage point fall in the fifth quarter post the uncertainty shock (as opposed to 0.59 in the External Instrument SVAR model).

3.3. Comparing our results to the results from a non-instrumented recursively-identified SVAR

We compare our results from our preferred model, the Internal Instrument SVAR, with those from a non-instrumented recursively-identified SVAR (see Fig. 4), where the uncertainty index (as opposed to the instrument) is ordered first as is standard in other New Zealand studies (for example, Greig et al. (2018); Tran et al. (2019)).[21] The

short- and medium-term horizons. We also estimated our model using the Local Projections approach and we can confirm the estimated impulse responses are identical at the short- and medium-term horizons; local projection impulse response estimates are available from the authors on request.

[20] As Fig. 2 showed the instrument is a strong one, we feel we do not need to adjust the confidence intervals to take into account weak instruments.

[21] In the non-instrumented recursively-identified SVAR, the instrument is not included in the model at all.

solid line in each graph in Fig. 4 is the impulse response from the non-instrumented recursively-identified SVAR and the shaded area represents the associated 90 per cent confidence intervals. The dot-dash line is the impulse response from the Internal Instrument SVAR. The impulse responses are broadly similar for all the variables except the output gap: the Internal Instrument SVAR estimates that a one-unit uncertainty shock has a peak impact of a 0.96 percentage point reduction in the output gap. In contrast, the non-instrumented recursively-identified SVAR estimates a peak 0.41 percentage point reduction. The estimate from the non-instrumented recursively-identified SVAR is in line with other estimates in New Zealand using (non-instrumented) recursive identification. For example, Greig et al. (2018) find, three to four quarters after the initial one-unit shock to their various domestic uncertainty measures, a peak impact of between −0.2 and −0.4 percentage points on the output gap. Tran et al. (2019) find a one standard deviation uncertainty shock decreases output, at most in a quarter, by 0.3 percent; Ryan (2025) finds a peak impact of −0.2 percentage points on the output gap from a one standard deviation uncertainty shock. Our general finding that non-instrumented recursively-identified SVAR results in attenuation bias is consistent with the findings of Carriero et al. (2015), Husted et al. (2020), Ha et al. (2022) and Kim (2019), who all find uncertainty shocks have larger impacts when the impacts are measured using External Instrument SVARs rather than non-instrumented recursively-identified SVARs.

3.4. Clarifying how uncertainty shocks transmit to output and prices

In order to understand how uncertainty shocks transmit through the economy, we augment our model with some additional variables from the *Quarterly Survey of Business Opinion*.[22] We reestimate the Internal Instrument SVAR model by adding seven new variables ($Y*_t$) to the original six variables in the model (Y_t) (plus the instrument). So the model is now estimated on the dataset: $[m_t, Y_t, Y*_t]$. Three of the newly-added variables relate to what firms expect to happen in the future, specifically:

1. The net percent of firms that expect their investment in plant and machinery will increase over the next 12 months.
2. The net percent of firms that expect their investment in buildings will increase over the next 12 months.
3. The net percent of firms that expect the general business situation in New Zealand to improve over the next six months.

We also include two further questions about experiences in the survey quarter to help us understand the channel through which uncertainty shocks transmit through the economy:

1. The percent of firms that reported demand as the single biggest factor limiting their ability to increase turnover.
2. The percent of firms that reported finance as the single biggest factor limiting their ability to increase turnover.

Finally, we include two questions about expected prices and costs to understand our inflation and interest rate results:

1. The net percent of firms that report they expect to increase their prices in the coming quarter.
2. The net percent of firms that report they expect to increase their costs in the coming quarter.

Fig. 5 shows the response to the uncertainty shock of (i) the three expected activity measures, (ii) the percent of firms reporting demand and finance as limiting factors, and (iii) the expected price and cost increase measures. The figure shows that, post the uncertainty shock, on aggregate, the firms' assessment of the economic outlook/ business situation worsens (see the *Economic Outlook* sub-figure), as does experienced demand (leading more firms to answer demand as the factor limiting turnover; see the *Demand* sub-figure). The concern about demand and the economic outlook/ business situation sees investment intentions for both buildings, and plant and machinery fall; see the *Building Investment* and the *Plant Investment* sub-figures. We do not find a noticeable impact from uncertainty on firms reporting finance as the limiting factor (see the *Finance* sub-figure) suggesting demand is the more important channel through which investment is muted. We will discuss the response of the cost and pricing intentions variables in the next section.

[22] The idea to look at the role expectations variables play in transmitting the uncertainty shock comes from Kamber et al. (2016).

3.5. Interpreting the response of inflation and interest rates

Using both the Internal and External Instrument SVAR models we saw that the uncertainty shock is initially associated with an increase in inflation (see Figs. 2 and 3). Further, both models also show an initial increase in the 90-day interest rate post the uncertainty shock before eventually falling. There is consistency between the initial responses of interest rates and inflation to the uncertainty shock given New Zealand's institutional settings. We note that the Reserve Bank of New Zealand's main policy objective was low inflation from 1990 to 2017, the bulk of our sample period. Therefore, if inflation increases initially we would expect interest rates to rise.

Our reported initial increases in the interest rate and inflation are consistent with Fasani and Rossi (2018). They show, using a New Keynesian DSGE model where the Taylor rule incorporates interest rate smoothing, that inflation initially increases following an uncertainty shock.[23] If it is assumed that the central bank does not respond to output in the Taylor rule (so the central bank only responds to the inflation pressures generated by the uncertainty shock, not to the fall in output owing to the fall in demand), the model of Fasani and Rossi (2018) generates an initial increase in the nominal interest rate post the uncertainty shock. Assuming that the central bank does not respond to output in the Taylor rule would be consistent, as we noted above, with the Reserve Bank of New Zealand's main policy objective of inflation targeting. Fasani and Rossi (2018) note the inflationary impact of the uncertainty shock in their model comes from an upward pricing bias when uncertainty increases: firms set higher prices to protect their profit margins. Other papers have also postulated this channel. In explaining their empirical findings that inflation increases post an uncertainty shock, De Santis and Van der Veken (2025) make a similar argument: firms bias their prices upwards to avoid being caught with low prices if the recession does not occur. In a survey article of uncertainty's effects, Castelnuovo (2023), citing the work of Fernández-Villaverde et al. (2015) and others, also notes this as a channel through which uncertainty can be inflationary.[24]

Consistent with our result that inflation initially increases post the uncertainty shock, in the *Pricing intentions* subfigure of Fig. 5, we see an increase in the number of firms expecting to increase prices initially post the uncertainty shock. The striking result in Fig. 5, however, is seen in the *Cost expectations* sub-figure: there is a large increase in the number of firms expecting cost increases initially post the uncertainty shock. Based on this result, we hypothesise another channel for the increase in inflation post the uncertainty shock. This channel is a variant of the channel set out above: it involves firms using higher prices as a form of 'insurance' in an uncertain time. Some of the

[23] In their model, it is only if interest rate smoothing is not assumed that inflation falls post the uncertainty shock. The authors argue assuming interest rate smoothing is more 'realistic' (p. 143).

[24] Additionally, Fratto and Uhlig (2020), Born and Pfeifer (2021), Kumar et al. (2021) and Beckmann and Czudaj (2024) provide empirical and/or theoretical support for uncertainty shocks being inflationary.

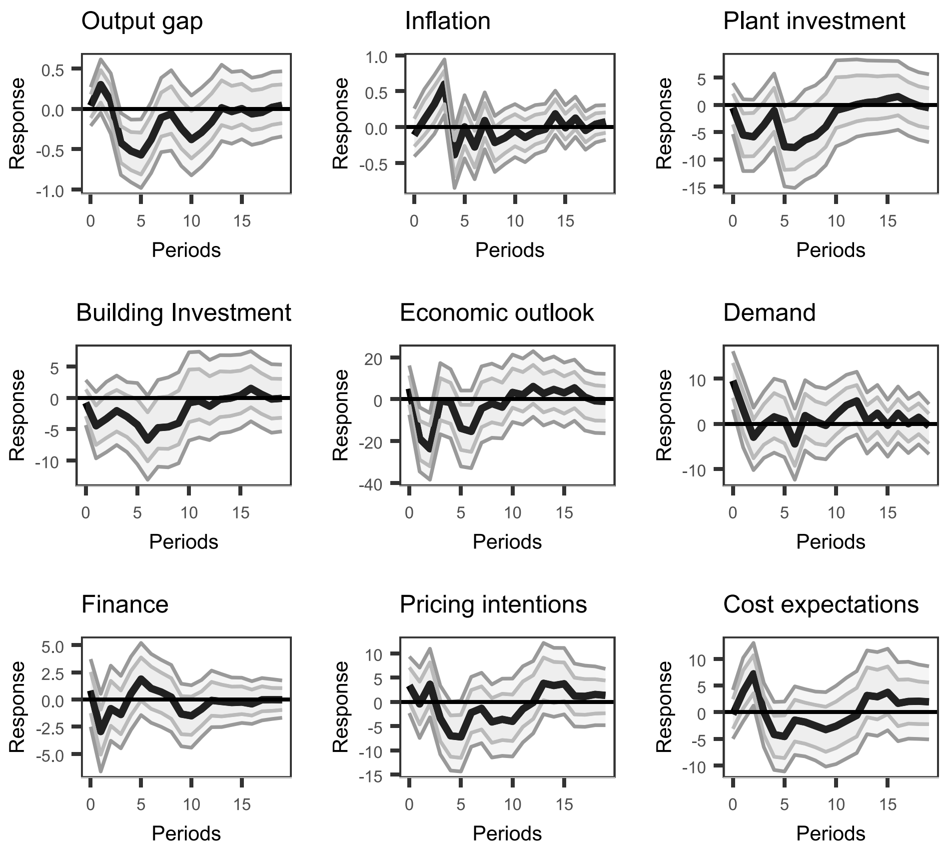


Fig. 5. Internal Instrument SVAR: business survey measures.
Notes: The dark grey and light grey areas represent 68% and 90% confidence intervals based on a wild bootstrap using 10,000 replications. Notes on subtitles are as follows. *Plant investment*: The net percent of firms that expect their investment in plant and machinery will increase over the next 12 months. *Building investment*: The net percent of firms that expect their investment in buildings will increase over the next 12 months. *Economic outlook:* The net percent of firms that expect the general business situation in New Zealand to improve over the next six months. *Demand*: The percent of firms that reported demand was the single biggest factor limiting their ability to increase turnover. *Finance*: The percent of firms that reported finance was the single biggest factor limiting their ability to increase turnover. *Pricing intentions*: The net percent of firms that expect to increase their prices in the next quarter. *Cost expectations*: The net percent of firms that expect increased costs in the next quarter. All responses are percentage points. The impulse responses to the uncertainty shock are derived via the Cholesky decomposition of $\sum_{\tilde{\eta}\tilde{\eta}} = E[\tilde{\eta}_t \tilde{\eta}_t']$, where $\tilde{\eta}_t$ are the reduced form residuals from a VAR estimated on a dataset of the instrument (ordered first) and then the uncertainty index, the change in the share price, the output gap, inflation, the interest rate and the exchange rate (TWI), plant investment, building investment, economic outlook, demand, finance, pricing intentions, cost expectations.

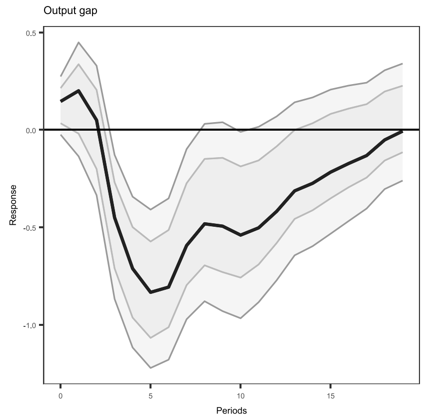
uncertainty events used in constructing our instrument are natural disasters. Natural disasters will potentially disrupt supply chains for long periods, reducing the availability of inputs and therefore driving up costs for firms. Firms, therefore, might increase prices owing to actual increased costs, but also pre-emptively increase prices further (to protect margins) given uncertainty about future cost increases that may occur. Beckmann and Czudaj (2024) discuss this channel in the context of COVID-19 and the Russian invasion of Ukraine.

3.6. Sensitivity tests

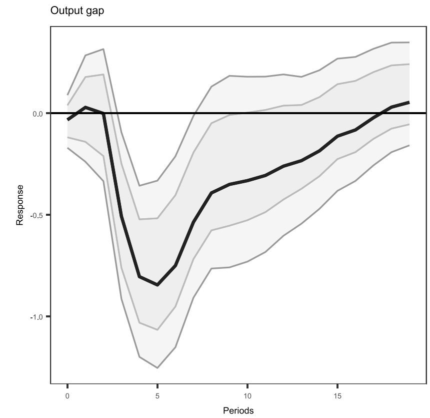
To test the sensitivity of our results to the construction of our instrument we run numerous robustness tests using the baseline Internal Instrument SVAR model in Section 3.2. The first is to exclude the two uncertainty events that occur just before significant downturns in economic activity; namely 1990Q2, which predates the early 1990s recession, and 2009Q3, which predates the Euro crisis. Although our instrument appears exogenous to contemporaneous economic activity shocks (see Table 2), it is worth testing the sensitivity of our results to omitting these quarters as the Internal Instrument SVAR model requires lead exogeneity of the instrument. For the second robustness test, we use a qualitative/binary version of the instrument: if the quarter is one of our uncertainty events (see Table 1), the instrument is assigned a value of one (rather than the value of our uncertainty index in that quarter), otherwise the quarter is assigned a value of zero. The peak impact on the output gap was −0.83 and −0.85 percentage points respectively in these two robustness tests (see Figs. 6(a) and 6(b)). To satisfy the reader that our results do depend on the instrument, we also conducted a placebo test as per Lagerborg et al. (2023). We randomly reshuffled our instrument event dates 1000 times and reran the model each time (so different quarters are allocated zero and the value of the uncertainty index for that quarter, but in proportion to the original instrument). The median impulse response and the median 90 percent confidence intervals across the 1000 simulations are plotted in Fig. 6(c) for the output gap. We see that the median confidence intervals suggest that uncertainty has no significant effect on output, whilst the estimated magnitude of the effect of uncertainty on output as presented by the median impulse response is relatively small. These results suggest, therefore, that the statistically significant effect we do find on output from the uncertainty shock using our actual instrument, which is of a relatively large magnitude, is not by chance.

A fourth robustness test we carry out is to replace the output gap in the model with household consumption and private investment.[25]

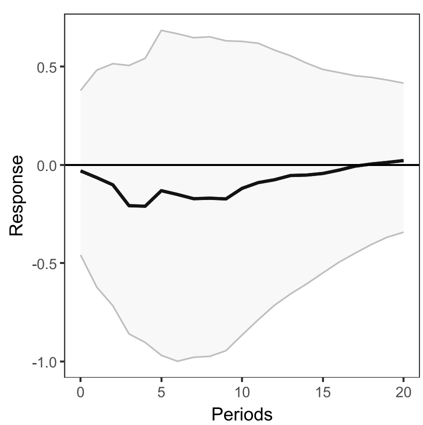
[25] As with all the original variables in the model (except the quarterly change in stock prices), we detrend consumption and investment. We do this



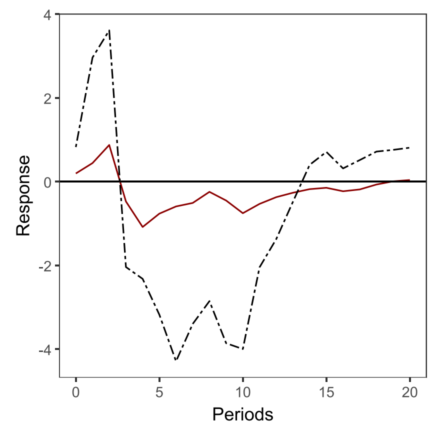
(a) Instrument with 1990Q2 and 2009Q3 removed



(b) Binary instrument



(c) Placebo instrument



(d) Consumption and investment responses

Fig. 6. Responses of the output gap to a one-unit shock to uncertainty: Internal Instrument sensitivity tests.
Notes: In subfigures (a) and (b), the dark grey and light grey areas represent 68% and 90% confidence intervals based on a wild bootstrap using 10,000 replications. In subfigure (c), we report the median impulse response and the median 90% confidence intervals from the set of results generated by reshuffling uncertainty events and rerunning the Internal Instrument SVAR 1000 times. In subfigure (d), the solid red line is the household consumption response to an uncertainty shock; the broken black line is the private investment response to an uncertainty shock. These responses come from the Internal Instrument SVAR, where consumption and investment are substituted for the output gap in the original model.

Theory suggests that investment should be more affected by the uncertainty shock than consumption. Under heightened uncertainty, firms should ‘wait and see’ before embarking on irreversible investment (Dixit, 1992). In contrast, consumption should react less if some part of consumption reflects lifetime income considerations or necessity. The impulse responses are plotted in Fig. 6(d). At peak impact, we see that the uncertainty shock reduces investment by 4.3 percent and consumption by 1.1 percent. These differential responses are consistent with expectations and give us confidence in our measure of uncertainty and the quality of the instrument. One note of caution with these results is needed. New Zealand’s official quarterly national accounts only began in 1987Q2, thus the quarterly values we use for household consumption and private investment between 1985Q2 and 1987Q1 are our backcast based on the annual totals reported in Dalziel and Lattimore (2001) and using the QSBO Economic outlook measure and the QSBO firm investment intentions as quarterly indicators for consumption and investment respectively in the Chow–Lin procedure.

We detrended our inflation, interest rate and exchange rate variables using the Hodrick–Prescott (H–P) filter. As discussed earlier, we did this to account for the structural change that took place in New Zealand during our sample period.[26] Hamilton (2018) has criticised the H–P filter on account that: ‘(a) The Hodrick–Prescott (HP) filter introduces spurious dynamic relations that have no basis in the underlying data-generating process. (b) Filtered values at the end of the sample are very different from those in the middle and are also characterised by spurious dynamics’ (p 831). Our preference for the H–P filter comes from the comparative exercise conducted by Hall and Thomson (2021). Hall and Thomson (2021, abstract) finds with New Zealand data that, relative to the H–P filter, the Hamilton filter ‘produces greater volatilities and less credible trend movements during key economic periods’ and performs worse at the end of series.[27] Nevertheless, we feel reestimating our original internal instrument version of the model with inflation, and the interest and exchange rates detrended via the Hamilton (2018) method is a useful check. The impulse responses are presented in Fig. 7. The peak impact on the output gap was −0.82 percentage points as opposed to −0.96 in our original model. The

owing to the large structural change in the New Zealand economy in the 1980s and early 1990s. We detrend the series using the H–P filter.

[26] We also detrended output to create the output gap but for this we used the Kamber et al. (2018) method.

[27] Franke et al. (2025, p.12) also concludes the H–P filter outperforms the Hamilton filter, noting the Hamilton filter ‘carries the risk of serious misperceptions during certain stages of the economic cycle’.

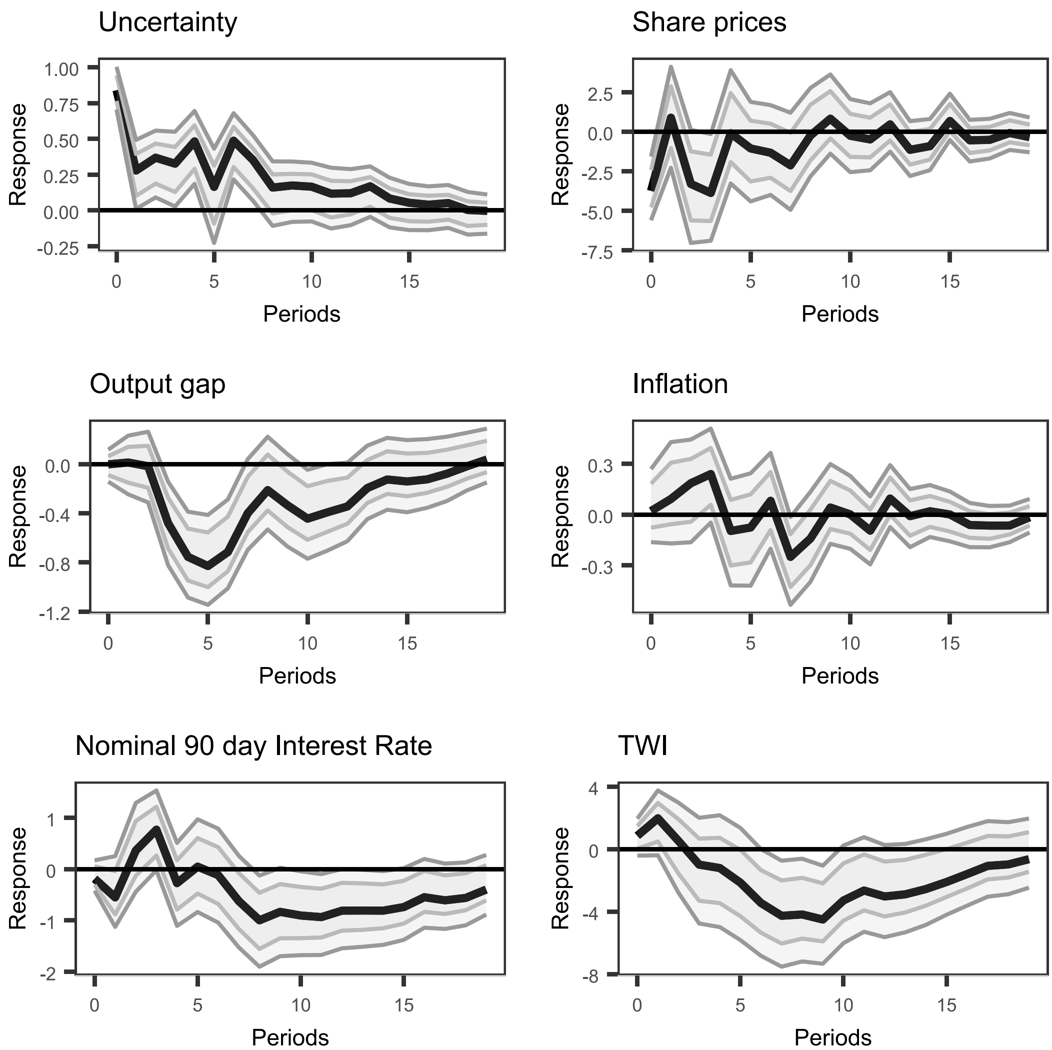


Fig. 7. Responses of the variables to a one-unit shock to uncertainty: Internal Instrument SVAR but with inflation and the interest and exchange rates filtered using the Hamilton (2018) filter.
Notes: The dark grey and light grey areas represent 68% and 90% confidence intervals based on a wild bootstrap using 10,000 replications. The units of the responses are all percentage points, except the TWI which is percent and uncertainty which is index units. *TWI* stands for Trade Weighted Exchange Rate. The impulse responses to the uncertainty shock are derived via the Cholesky decomposition of $\sum_{\tilde{\eta}\tilde{\eta}} = E[\tilde{\eta}_t \tilde{\eta}_t']$, where $\tilde{\eta}_t$ are the reduced form residuals from a VAR estimated on a dataset of the instrument (ordered first) and then the uncertainty index, the change in the share price, the output gap, inflation, the interest rate and the exchange rate (TWI).

response to the uncertainty shock of other variables is qualitatively similar to the original model, although in the Hamilton filter version of the model: (i) the initial increase in inflation is more persistent and (ii) the initial increase in the interest rate is delayed.[28][29]

3.7. *The contribution of uncertainty to the output gap over different horizons*

We now examine the extent to which uncertainty shocks matter for the variation in the output gap over different time horizons. The traditional way of the doing this is the forecast error variance decomposition. In the External Instrument SVAR, the forecast error variance decomposition relies on the structural shocks being invertible. We have established that this is probably not the case in our application (see Table 3). Earlier we did not, however, reject recoverability; again, see Table 3. Under the weaker assumption of recoverability, the Forecast Variance Ratio, FVR, statistic developed by Plagborg-Møller and Wolf (2022) can be used. For variable y_i at horizon h, the estimated lower and the upper bounds of the FVR can be stated as:

[28] We acknowledge the H–P filter plays a role in the construction of our instrument. Specifically, large uncertainty values relative to the trend in uncertainty identified using the H–P filter are termed uncertainty peaks and considered for inclusion in the instrument series. We redo our instrument creation process, but use the Hamilton filter to identify the trend. Under this procedure, 2009Q3 and 2014Q2 are no longer classed as uncertainty peaks and are dropped from the instrument list. If we estimate the original internal instrument model with this revised instrument, we find the peak impact on the output gap is −0.88 percentage points, only slightly smaller than −0.96 with our original instrument.

[29] There is one final robustness test we do. In constructing the Internal Instrument SVAR, we include lags of the instrument and the other variables in the equation where the instrument is the dependent variable. Bruns and Lütkepohl (2025) say one could also consider not including the lags of these variables in this equation. If the lags are not included, the peak impact of the output gap is −0.88.

Table 4
The contribution of uncertainty to the output gap over different horizons.

Model	Four quarters	Eight quarters	16 quarters
FVR - lower bound	8%	33%	34%
Recursive SVAR - FEVD	12%	19%	21%

Notes: *FVR - lower bound*: the lower bound of the forecast variance ratio for horizons 4, 8 and 16 quarters ahead. This is constructed as per Eq. (8) and follows Plagborg-Møller and Wolf (2022); *Recursive SVAR - FEVD*: the forecast error variance decomposition from the non-instrumented recursively-identified SVAR for horizons 4, 8 and 16 quarters ahead.

$$\left[\frac{1}{\hat{\alpha}_P^2} \times \frac{\sum_{j=0}^{h-1} \widehat{\mathrm{Cov}}(y_{i,t}, \tilde{m}_{t-j})^2}{\widehat{\mathrm{Var}}(y_{i,t+h}|\{Y_\tau\}_{-\infty<\tau\leq t})}, \frac{1}{\hat{\alpha}_Q^2} \times \frac{\sum_{j=0}^{h-1} \widehat{\mathrm{Cov}}(y_{i,t}, \tilde{m}_{t-j})^2}{\widehat{\mathrm{Var}}(y_{i,t+h}|\{Y_\tau\}_{-\infty<\tau\leq t})}\right] \quad (8)$$

As noted in Section 3.2, $\tilde{m}_t$ are the residuals from the regression of the instrument, m_t, on lagged values of itself and the other variables in the model (Y_τ). As with Eq. (7), the bounds of the FVR depend on the two estimates of a scalar α^2: $\hat{\alpha}_P^2$ and $\hat{\alpha}_Q^2$. We noted in Section 3.2 $\hat{\alpha}_P^2$ would be closer to the true value of α^2 if we had a perfect instrument for the uncertainty shock. While $\hat{\alpha}_Q^2$ would be closer to the true value of α^2 when the uncertainty shock is invertible. These statements imply the lower bound on the FVR is closer to the true FVR if we had the perfect instrument, while the upper bound on the FVR is closer to the FVR if the uncertainty shock were invertible. Plagborg-Møller and Wolf (2022) note the true FVR lies somewhere between these two bounds.

Table 4 presents two estimates of uncertainty's contribution to the output gap's forecast variance at various horizons. The first row of Table 4 is the estimates of the lower bound of the FVR, constructed as set out in Eq. (8); the second row of Table 4 is the estimate of the forecast error variance decomposition from the non-instrumented recursively-identified SVAR. Note we only report the lower bound of the FVR, because as noted above, the upper bound is only close to the true FVR when the degree of invertibility is larger, and we do not think the degree of invertibility in our application is large (see the bounds estimates in Table 3).[30]

Table 4 has two key takeaways. The first is that over the near-term forecast horizon (four- quarters-ahead), uncertainty shocks have a moderate effect on the output gap, but this increases at longer forecast horizons. Secondly, at the eight- and 16- quarters-ahead forecast horizons, the lower bound of the FVR estimates that uncertainty shocks make a much larger contribution to the forecast variance in the output gap than estimated via the forecast error variance decomposition based on the non-instrumented recursively-identified SVAR.

Greig et al. (2018) and Tran et al. (2019) estimate the contribution of New Zealand uncertainty shocks to the variance of the forecast error in the New Zealand output gap using forecast error variance decompositions from recursively-identified SVARs. Greig et al. (2018) report uncertainty shocks explain between 11%–31% of the four–quarter–ahead forecast error variance of the output gap, while at the eight–quarter-ahead horizon uncertainty shocks explain between 13%–35% of the variance in the forecast error in the output gap. The range given for these estimates at each forecast horizon reflects that Greig et al. (2018) estimate their model with eight different uncertainty measures. For their uncertainty measure that is constructed from the same dataset as ours (the *Quarterly Survey of Business Opinion*), but using sector-level rather than firm-level data to construct the uncertainty index, they estimate at the four– and eight–quarter–ahead forecast horizon, the contribution of uncertainty shocks to output gap fluctuations is 22 percent and 28 percent respectively.[31] Tran et al. (2019) report New Zealand uncertainty explains between 20 and 32 percent of fluctuations in the output gap, depending on the uncertainty measure, at the four-quarter-ahead forecast horizon.

4. Conclusion

The last 15 years have seen a large number of studies studying the effects on the macro-economy of uncertainty shocks. In order to identify the effects of the uncertainty shock, most of these studies have made an assumption that is hard to defend: uncertainty, and macroeconomic and financial variables do not affect each other contemporaneously. Studies of the effects of uncertainty shocks on the New Zealand economy are no exception to this rule. To relax this assumption, this paper shows how a simple instrument can be constructed for a small open economy that meets both the exclusion and relevance conditions required of an instrument. Importantly the instrument does not rely on asset prices that might be contaminated in a small open economy, but rather employs a narrative-based approach. Using this instrument, we establish that previous New Zealand studies may have underestimated uncertainty's effect on the output gap.

Although the first in a New Zealand context, this paper is not the first to employ instrumental variables to examine the effects of uncertainty shocks in the SVAR set up. We are, however, the first paper to our knowledge to check for invertibility of the uncertainty shock. Invertibility of the uncertainty shock is a key requirement for the validity of the impulse responses and the forecast error decompositions from the External Instrument SVAR. Invertibility is not an assumption, however, that is guaranteed to hold when studying uncertainty's effects, given uncertainty as measured at a point in time is likely to reflect concerns about future policy or economic fundamentals. Indeed, using a formal statistical test, we find that invertibility does not hold and we change our modelling framework accordingly. Specifically, we use the Internal Instrument SVAR, a framework that does not rely on invertibility. Comparing the results from the Internal and External instrument SVARs, we show that the estimated impulse responses of output to an uncertainty shock are materially different. This difference illustrates the effects of ignoring the invertibility requirement of the External Instrument SVAR when studying uncertainty.

Our results contain an important message for researchers using instrumental variables in the SVAR framework to study uncertainty (or indeed, any other perception-based variable, such as sentiment, whose fluctuations may in part capture expectations about future developments): invertibility needs to be tested for and the results of these tests need to inform the appropriate empirical framework. If invertibility is ignored, the impact of uncertainty could be mismeasured. Further, because we find uncertainty has a large negative effect on output but a positive effect on inflation, our results contain two important messages for policymakers in small-open economies with a floating exchange rate. The first is, given uncertainty is more detrimental to output than previously thought, if policymakers wish to stabilise the business cycle post increases in uncertainty, they will need to provide significant stimulus. Secondly, because our output and inflation results suggest a conflicting course of action for central banks with a dual mandate, central bankers will need to decide which objective to put more weight on in making their monetary policy decisions when faced with an uncertainty shock.

[30] We think this is the reason why the upper bound estimates we get for uncertainty's contribution to the forecast variance in the output gap using Eq. (8) are implausibly high.

[31] The key difference between our firm-level construction and the sector-level construction of Greig et al. (2018) is discussed in Section 1 of the Online Resource to this paper.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work one author used ChatGPT in order to review selected sentences to improve clarity. We also asked ChatGPT to proofread the final document. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2025.107294.

Data availability

The raw firm-level data used for the uncertainty index in this study cannot be shared for confidentiality reasons. Instructions for how other researchers can obtain the raw data are available from the authors. The code and the data used once the firm-level data has been processed into the uncertainty index are available at Mendeley, https://data.mendeley.com/datasets/8s455j6h7c/1.

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