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How Inflation Targeters (Can) Deal with Uncertainty

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1. Why Worry about Uncertainty?

This paper was motivated by the fact that the methods employed by inflation targeters to deal with uncertainty do not receive as much attention as other parts of the inflation targeting strategy. This insufficient attention does not correspond to the impact that these methods, or a lack of them, can have on the quality of decisions about interest rates. There are two essential reasons why inflation targeters need a well-designed methodology for dealing with uncertainty. Firstly, inflation targeting is a forward-looking strategy. Prior to setting interest rates, monetary policy makers need the best possible inflation forecast, given the constraints of imperfect knowledge about the current state of the economy and even less perfect knowledge about future economic events. Improper dealing with uncertainty can lead to defects in the decision-making process, and, as a result, sub-optimal policy reactions can burden the economy with otherwise avoidable costs, for example an excessive output loss.[1] Secondly, a well thought out methodology for dealing with uncertainty is easily explained to the general public. Any ad hoc or implicit treatment of uncertainty necessarily leads to confusion on the part of the financial markets and the public, who have difficulties understanding why a certain decision about interest rates was taken. This confusion can prevent the financial markets from deriving correctly the future direction of monetary policy from the inflation forecast, and the general public from distinguishing the consequences of unforeseen external shocks from policy errors. The subsequent loss of monetary policy credibility can be costly for the economy.[2]

It is not easy to develop a well-designed methodology for dealing with uncertainty and to communicate it effectively to the general public, since the complete treatment of uncertainty is a very complex issue. Research papers often describe inflation targeting as inflation-forecast targeting, where

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[1] See (Smidkova, 2003) for a summary of the implications of various types of uncertainty for the optimality of monetary policy decisions.

[2] This is analysed in (Geraats, 2001).

the targeted inflation forecast is fully based on a model and normally distributed shocks.[3] Although recent research has made significant progress by approximating monetary policy decisions with Bayesian models that work with more complex distributions and with robust control methods related to model uncertainty,[4] the research papers still cover only a subset of the uncertainties faced by monetary policy makers. Monetary policy makers claim that they do not follow simplistic normative recommendations produced by models[5] and emphasise that economic research should focus on a much broader set of uncertainties. Interestingly, the economic research itself provides enough evidence that monetary policy makers consider more factors than the model-based forecasts and the above-mentioned subset of uncertainties. Otherwise, it would not be so difficult to explain their decisions with model simulations and policy rules.[6] The missing part in the picture that the research papers draw is consideration of various types of so-called Knightian uncertainty.[7] This type of uncertainty is not easily approximated with a model or statistical distribution and can be related to the forecasting model itself or to the expert judgement about unknown factors. Monetary policy makers are aware of the fact that forecasting the future is very complicated, and, consequently, they employ a variety of methods, not just model-based ones, to deal with uncertainty, however informal or implicit this may be.[8]

The fact that the methodology for dealing with uncertainty is a very complex issue implies that it is very difficult to describe fully. Hence, it is sometimes worked with implicitly during the decision-making process. While it is easy to find papers describing a forecasting system of an inflation-targeting central bank, it is much more difficult to find a systematic description of how inflation targeters deal with uncertainty. There are costs involved if the methods employed by inflation targeters to deal with uncertainty are not treated explicitly. First, inflation targeters cannot compare notes about these methods as easily as they can about their forecasting mo-

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[3] Batini and Haldane (1999) and Svensson (1996) illustrate the features of inflation targeting in this set-up.

[4] Cogley, Morozov and Sargent (2003) and Sims (2002) draw a parallel between the behaviour of monetary policy makers and Bayesian econometrics. Tetlow and von zur Muehlen (2000) apply robust control methods to deal with model uncertainty. Cagliarini and Heath (2000) show that in papers on robust control methods an inadequate decision rule is used. Similarly, Goodhart (2003) suggests that minimising the costs of the worst possible scenario cannot approximate the behaviour of monetary policy makers. Both Cagliarini and Heath (2000) and Tetlow and von zur Muehlen (2000) emphasise that the results of their analysis depend on the models selected for the analysis.

[5] Monetary policy makers also emphasise that it is not possible to use policy rules for normative recommendations. Issing (2002) points out that central banks must use frameworks that are much more complex than policy rules.

[6] Orphanides (1998), Smets (1999) and Tetlow and von zur Muehlen (2000) focus on explaining the differences between the behaviour of monetary policy makers and the actions suggested by policy rules by analysing the implications of different types of uncertainty.

[7] This concept is defined in (Knight, 1921).

[8] Blinder (1999), Freedman (1999) and Issing (1999) draw attention to the fact that the economic research does not solve the problems of Knightian uncertainty, which is very difficult to approximate with statistical distributions and is often related to the forecasting model itself.

dels. As a result, the methods for dealing with uncertainty might not be employed and improved as effectively as they could. Second, central banks that start targeting inflation may underestimate the importance of these methods. These are usually central banks in emerging economies, where the uncertainties related to the inflation forecast are much larger than in advanced market economies and where more attention should be paid to uncertainty, not less. Third, monetary policy may not be fully transparent. This is especially a problem in periods when uncertainty plays a more prominent role in decisions about interest rates than usual. A lack of transparency can reduce the efficiency of monetary policy actions. In addition, lower transparency can mislead the economic research that analyses monetary policy under uncertainty.[9]

These costs should be prevented by starting a discussion of the methods dealing with uncertainty explicitly in the context of inflation targeting. As was said, the methodology for dealing with uncertainty is usually very complex, and hence a simple framework is needed to organize this discussion. The aim of this paper is to suggest one comparative framework that might do the job. The suggestion is to describe the methods available to deal with uncertainty for each element of the interest rate decision-making process. The suggested comparative framework is designed in line with the know-how of "decision analysis". The concepts of decision analysis have been employed by decision-makers leading important institutions in many important areas when they have needed to make good decisions under uncertainty.[10] According to decision analysis, every decision-making process consists of certain elements that are all necessary for taking good decisions. These elements present very different types of information, yet they must still be put together in a consistent picture prior to the decision.

Examples of the above-mentioned elements include variant model-based forecasts, the subjective probabilities of alternative scenarios and the pay-offs derived from loss functions. Like other decision-makers, monetary policy makers employ them all in order to set interest rates. This does not mean that all the elements are treated explicitly prior to every monetary policy decision. It does mean, however, that all the elements have a significant impact on the quality of the decision even if treated implicitly. The following example illustrates the importance of dealing with uncertainty explicitly. A "decision matrix" is used to demonstrate the example.

In the first case, the interest rate decision is based solely on the most likely scenario (*Table 1*). One can think of it as follows. One set of assumptions was defined. The central forecast was produced with the core model, working with a fixed-rate assumption. In addition, the model was used to estimate the implications of two alternative policy reactions.[11] The pay-off of each outcome was then evaluated according to the policy maker's loss function. The policy reaction that yields the best pay-off, which is repre-

[9] One can observe from the recent debate – as outlined, for example, by Cagliarini and Heath (2000) and Tetlow and von zur Muehlen (2000) – that it is not easy for researchers to approximate the methods used by monetary policy makers to deal with uncertainty.

[10] Beroggi (1998), Clemen (1996) and Skinner (1999) provide a good introduction to decision theory and decision analysis.

TABLE 1 One-Column Decision Matrix: "The Best of the Most Probable"

Possible reactions	
Reduction in interest rates	1.216
No change in interest rates	*1.212**
Increase in interest rates	1.215

Notes: See (Smidkova, 2004) for calculations.
* This is the central forecast.

TABLE 2 Complex Decision Matrix: "The Best Expected Value"

Probability	***0.1***	***0.5***	***0.4***	
Alternative *assumptions* Possible reactions	**Deflation pressures**	**Neutral pressures**	**Inflation pressures**	**Expected pay-off**
Reduction in interest rates	13.207	1.216	1.431	2.501
No change in interest rates	13.432	1.212*	1.300	2.469
Increase in interest rates	13.663	1.215	1.175	2.444

Notes: See (Smidkova, 2004) for calculations.
* This is the central forecast.

sented by the lowest value of the loss function, was selected. As a result, interest rates were left unchanged. In this case of no explicit dealing with uncertainty, the decision matrix consists of one column only. It is analogous to assuming that the model and all assumptions related to the forecast are certain.

In the second case, the decision-making process consists of more elements (*Table 2*), and consequently the decision matrix has more rows and columns. Three alternative scenarios were considered and a probability was attached to each of them. These probabilities are usually called subjective probabilities, since they cannot be estimated easily. The expected pay-offs were computed and the reaction with the best expected pay-off, which is represented by the lowest value of the expected loss function, was selected. As a result, interest rates were increased.

The comparison of the two above-described cases shows that methods dealing with uncertainty are important for monetary policy makers in situations where the certainty equivalence principle does not hold.[12] In the exam-

[11] It is worth noting that a similar approach can be used if the model includes endogenous monetary policy. In that case, three different reaction functions can be used, representing neutral, slow and aggressive responsiveness of monetary policy to shocks. Both approaches to inflation forecasting are possible. Don (2001) argues that a conditional forecast is more suitable for institutions that can affect the whole economy and that an unconditional forecast causes a difficult decision problem for them. Archer (2003) claims that central banks should base their forecasts on models with endogenous monetary policy. The survey presented in (Smidkova, 2003) shows that central banks use both approaches in reality.

[12] In line with Brainard (1967), the certainty benchmark is defined as the policy reaction that would be optimal under certainty. Under uncertainty, the optimal policy reaction is different. According to the certainty equivalence principle, certain types of uncertainty, such as linear symmetric risks, do not change the optimal policy. This is called the equivalence principle.

ple, the alternative sets of assumptions were asymmetric and the probabilities of the alternative sets of assumptions were significant and asymmetric. Hence, once the uncertainty related to the central forecast was put into the picture, a different decision was taken which was closer to optimum than in the case of neglecting uncertainty. The example illustrates the importance of treating uncertainty explicitly. Imagine that only the central forecast was published in the second case. Without knowing the alternative sets of assumptions and subjective probabilities, observers most probably did not understand why interest rates were increased.

It follows that the suggested framework for comparing the methods employed to deal with uncertainty is general enough to encompass methods that can differ quite substantially. They range from producing simulations with the core forecasting model to attaching subjective probabilities to alternative sets of assumptions to computing pay-offs from often implicit loss functions. It is worth noting that although it looked quite simple in the example, the information represented by the various components of the decision matrix is not always easily obtained. Specifically, it is not straightforward at all to define the alternative sets of assumptions. Although there are model-based methods available to help with this task, such as sensitivity analysis, at the end of the day the definition of alternative sets of assumptions relies enormously on the intuition and judgement of experts and monetary policy makers.

2. The Methods Available to Deal with Uncertainty

The main purpose of this section is to present in a comprehensible way the findings of a survey of the methods available to monetary policy makers for dealing with uncertainty.[13] Three distinct sources have been surveyed. First, economic research on monetary policy under uncertainty provides a background for dealing with certain types of uncertainties that can be incorporated into the model framework.[14] Second, decision analysis offers various methods that are less mathematically rigorous and rely more on intuition and judgement.[15] Some forecasters have already used the decision theory framework to recommend methods of presenting the forecast uncertainty to decision makers.[16] Third, the "real-life" methods of five inflation targeters show that monetary policy makers do not limit themselves to producing the central forecast when deciding about interest rates. They typically rely on a combination of various methods to deal with uncertainty. For example, several central banks attach subjective distributions to

[13] The background to the survey is described in (Smidkova, 2003).

[14] Cogley, Morozov and Sargent (2003), Sims (2001) and Wallis (2004) offer sophisticated econometric tools to deal with uncertainty that can be expressed within the model.

[15] Clemen (1996), Skinner (1999) and Wright and Goodwin (1998) give examples of tools that work with subjective probabilities, such as the decision matrix, the decision tree and the pay-off table.

[16] Don (2001) uses decision theory terminology and argues that the role of the forecast is to help reach competent decisions.

the central forecast in order to produce fan charts. Several banks use alternative scenarios to deal with uncertainty about important external factors such as commodity prices. And some let a group of experts vote about the policy recommendation prior to the meeting of the monetary policy makers.

The methods compiled from the survey have been grouped together into the following four sections corresponding to elements of the interest rate decision-making process:
– producing the central forecast by the expert group,[17]
– conducting robustness analysis[18] by the expert group,
– attaching subjective probabilities and pay-offs by the expert group,
– deciding about interest rates by monetary policy makers.

It is worth noting that the interest rate decision-making process need not be organized in the same order. Central banks often design their decision-making process as iterative. Some parts of the decision-making process can even be repeated several times.[19] These iterations usually aim at modifying the assumptions of the central forecast in order to better reflect the scenario with the best expected outcome. Without these iterations, the central forecast could not play a prominent role in the actual decision and in external communication. Asymmetric risks attached to the central forecast are one possible reason for initiating changes in the assumptions of the central forecast.[20] Since producing the central forecast with balanced risks through an iterative process is a time-consuming process, the full forecasting rounds are typically less frequent than the actual monetary policy decisions. As a result, some methods for dealing with uncertainty, such as attaching subjective probabilities, can play a more prominent role between the two forecasting rounds.

2.1 Producing the Central Forecast

The main purpose of producing the central forecast is to create a benchmark for the monetary policy debate. The central forecast is typically produced with one of the following three tools: expert know-how, a deterministic model or a stochastic model. The more sophisticated the forecasting tool is, the broader the set of technical methods dealing with uncertainty can be employed (*Table 3*). First, all the tools allow for the compilation of a list of uncertainties related to the central forecast. The list usually consists of uncertainties that have a large impact on the forecast and also a high

[17] Monetary policy makers often participate in the meetings of the expert groups.

[18] Rosenhead and Mingers (2001) use a robustness matrix in order to organise the results of the robustness analysis. Sometimes the two terms are viewed as interchangeable.

[19] All five inflation targeters from the survey report strategies that are similar to the iterative strategy. For example, the Swedish Riksbank describes its decision-making process as follows. The main scenario and risks are mostly prepared by experts. If the Board disagrees with the outcome of the process, the main scenario or inflation forecast distribution can be adjusted.

[20] Monetary policy makers emphasise that asymmetry in risks poses a serious problem to them because the central forecast is then too far from the best expected outcome. They may try to reduce the potential asymmetry in risks during the monetary decision-making process. The author thanks C. Goodhart and L. Niedermayer for this comment.

TABLE 3 – Producing the Central Forecast

	Stochastic forecast	Model forecast	Expert forecast
Methods for dealing with uncertainty	– past values of forecasting errors – list of potential uncertainties produced – estimation statistics (if model was estimated) – sensitivity analysis – interval forecast available	– past values of forecasting errors – list of potential uncertainties produced – sensitivity analysis; estimation statistics (if model was estimated)	– experts report past values of forecasting errors – list of potential uncertainties produced
Examples	CMS, HSYB, KW	BoC, RBNZ, SR, BoE, CNB* (since 2002)	CNB* (prior to 2002)
Major pros	Full information set available for the next stages. Estimates of some uncertainties available.	Model gives framework for discussion. Central forecast gives clear benchmark to assess uncertainties.	Robust to the core model uncertainty. Know-how of modelling not necessary.
Major cons	Requires know-how of stochastic modelling. Explicitly represented uncertainties may interfere with further methods for dealing with uncertainty.	Central forecast does not necessarily indicate the optimal policy response. Requires know-how of modeling.	Incomplete information set makes it difficult to assess uncertainty in the next stages. Implicit treatment of model uncertainty makes further policy debate difficult.

Note: Abbreviations: BoE – Bank of England, BoC – Bank of Canada, CNB – Czech National Bank, RBNZ – Reserve Bank of New Zealand, SR – Swedish Riksbank. CMS – Cogley, Morozov, Sargent (2003), HSYB – Hall, Salmon, Yates, Batini (1999), KW – Wallis (2004).

* In this case, the method has not been applied to its full extent (explanation given in brackets).

probability. Second, if a model is used, extensive sensitivity tests and policy simulations, reflecting the sensitivity of the inflation forecast to the level of interest rates or to the specification of the reaction function, can be reported. Third, within the stochastic model framework, estimates of the uncertainties that can be represented within the core model are available together with the central forecast.

All methods aim at enlarging (and organizing) a supplementary set of information that is produced together with the central forecast. This stage is crucial, since the larger the set of supplementary information is, the more methods for dealing with uncertainty can be employed in the later stages of the process.

2.2 Conducting Robustness Analysis

This part of the decision-making process is designed to detect the scope of uncertainty related to the central forecast. By conducting robustness analysis, experts produce information that corresponds to elements of the so-called robustness matrix that is very similar to the matrix from the example in section 1 (Table 2). By defining alternative policy assumptions, they specify the rows of the matrix. By selecting the alternative sets of assumptions, they specify the columns of the matrix. By producing alternative forecasts for different rows and columns of the matrix, the experts obtain a full set of outcomes that can be compared. If the outcomes are close to the central forecast, the uncertainty faced by monetary policy makers is low. If they differ significantly, great care must be taken to make a good decision. It is often the case that the construction of the robustness matrix is done only informally and the conclusion about low uncertainty is reached without actually running the model several times.

The most difficult step is the compilation of the list of relevant uncertainties and the definition of the alternative sets of assumptions that form the columns of the matrix. As was mentioned, the more information is available from the previous stage of the process, the better. The tricky part is to select which uncertainties are relevant to the decision about interest rates. Recent economic research suggests that building all the relevant uncertainties inside the modeling framework and producing a stochastic distribution of all the possible outcomes instead of a more simplistic robustness matrix can be an option. However, the research does not so far offer a methodology for incorporating all the potential uncertainties into one framework.[21] Moreover, this approach can lead to problems with overstated uncertainty. Hence, experts cannot rely solely on the methods developed so far by the economic research and they have to specify their list of relevant uncertainties by using less formal approaches.

Which methods are available to select relevant uncertainties? According to our survey, there are various options on hand. For example, it is possible to develop a rule of thumb. Every potential uncertainty that could change the inflation forecast by x % or more could automatically qualify for the list of relevant uncertainties. Alternatively, it is possible to rely on intuition and to illustrate several economic problems that are currently being debated (even in this case, a relevant uncertainty should have a large potential impact on the inflation forecast and have non-negligible probability).[22] The following examples illustrate the potential candidates for the list of relevant uncertainties:

– assumptions about an influential exogenous variable whose future path is uncertain,
– residuals in an equation that is influential in the model and has large errors,
– a functional form of an influential equation that is subject to a structural break,
– the role of an influential equation that is over-written by off-model information,
– influential model components (e.g. a long-run solution) that are not consensual.

Once the list of relevant uncertainties has been compiled, experts face the second dilemma of how to group them together into several sets of al-

[21] Issing (2002) gives examples of the problems faced by monetary policy makers that cannot be dealt with using the currently available modeling methods.

[22] It is worth noting that the process of deciding which uncertainties are relevant should eliminate those that are not very likely and those that are not very influential. As a result, the problem of low-probability large extreme events that is analysed in Svensson (2003) should be eliminated.

TABLE 4 Computing Alternative Outcomes

	Distribution	Several alternatives	Description of risks by experts
Methods for dealing with uncertainty	– produces a distribution showing the second and third moments of the estimated uncertainty of the forecast	– several alternative outcomes approximate the scope of uncertainty related to the central forecast – the distribution of the outcomes with respect to the central forecast approximates the asymmetry of risks	– verbal description of risks related to the central forecast indicate which types of uncertainty are relevant to the decision
Examples	KW*, CMS* (in these two studies, off-model uncertainty is not considered), SR* (interval uncertainties specified for inputs to the inflation forecast), BoE, SR*	FD, BoC, CNB* (quarterly), RBNZ ("hawkish" and "dovish" sets in the initial stage)	CNB* (between quarterly forecasts)
Major pros	No need to group alternative assumptions into sets. Outcome is valuable for external communication.	Shows both inflationary and deflationary risks. Can approximate very atypical distributions.	No need to run the model several times.
Major cons	Relies too much on the pre-specified distribution. Requires attaching of subjective probabilities.	Difficult to group assumptions into sets. Difficult to use for external communication.	Impossible to approximate the best expected outcome.

Note: Abbreviations: BoE – Bank of England, BoC – Bank of Canada, CNB – Czech National Bank, RBNZ – Reserve Bank of New Zealand, SR – Swedish Riksbank. CMS – Cogley, Morozov, Sargent (2003), FD – Don (2001), HSYB – Hall, Salmon, Yates, Batini (1999), KW – Wallis (2004).
* In this case, the method has not been applied to the full extent (explanation given in brackets).

ternative assumptions. The grouping determines how many columns the (informal) robustness matrix has and also what the role of the central forecast is in the decision-making process. There is an obvious trade-off. On the one hand, a large number of sets is easy to generate, since each uncertainty can be treated separately, but this is more difficult to discuss. On the other hand, a small number of sets fosters an efficient policy debate, but is more difficult to construct since it requires quite a substantial debate about the suitable grouping. Due to this trade-off, inflation targeters, like other forecasting institutions, use between two and five alternative scenarios, preferring clearly a more efficient debate.[23] It is worth noting that inflation targeters use alternative sets even when they use probability distributions for representing uncertainty, because these distributions are constructed mainly in order to communicate uncertainty externally.

[23] Don (2001) also recommends a small number of scenarios in his paper about forecasting.

2.3 Subjective Probabilities and Pay-offs

Subjective probabilities and pay-offs are supplementary information that experts can provide to monetary policy makers in addition to robustness analysis. They are both important if experts are asked to recommend which policy decision to take. Without probabilities and pay-offs, it is not possible to evaluate which decision corresponds to the best expected outcome. Sometimes, when producing a forecast or conducting robustness analysis with a certain modeling framework, experts incorporate their views on pay-offs and probabilities inside the framework. Specifically, models with endogenous monetary policy or frameworks designed to produce fan charts fall into this category. Other modeling approaches do not require this, and if not revealed explicitly, the expert views on pay-offs and probabilities are not known to monetary policy makers at the time of their decision on interest rates.

When revealing the pay-offs, experts take into account two tools that are usually built into the inflation targeting strategy to deal with uncertainty: an inflation target interval and a list of caveats.[24] They need to decide if the circumstances are right to evaluate the outcome with respect to the mid-point of the target or whether the situation calls for some special action such as targeting the upper or lower band of the target. This decision is usually not reached mechanically and cannot be incorporated inside the model. Similarly, the probabilities of alternative sets of assumptions cannot be easily estimated and hence they are decided intuitively. That is why for these two problems the economic research cannot offer a complete solution. However, there are methods available to deal with the issue (*Table 5*). The experts can use some of the tools suggested by decision analysis. The most sophisticated tool offered by decision analysis to policy makers is to ask the expert group to reach a consensus. Alternatively, the experts can vote about the pay-offs and probabilities and their votes can then be averaged. The easiest way – followed by several inflation targeters – is to allow the experts to work with the pay-offs and probabilities implicitly and vote on the policy recommendation. In this case, monetary policy makers have access to the voting pattern and they can learn gradually over time about the subjective probabilities and pay-offs attached by the experts to the alternative outcomes.

No matter which tool is employed, it is always important to select the expert group carefully in order to deal with uncertainty efficiently. The expert group should have both an adequate size and a well-designed structure.[25] Specifically, the experts should not have the same background (e.g. it makes no sense to have only the modeling team voting). In addition to the modelers, other experts in the group should be able to offer detailed knowledge about problems that are on the list of relevant uncertainties. It follows that

[24] Mahadeva and Sterne (2000) describe a variety of inflation-targeting frameworks.

[25] Clemen and Winkler (2004) show that adding an expert to the group as well as adding methods improves the quality of decisions with diminishing returns, and that adding the expert helps more than working with an additional analysis method. Blinder and Morgan (2000) show that decisions about interest rates are better done by a group of experts.

TABLE 5 Pay-offs and Probabilities Attached by Experts

	Consensus	Averaging of votes	Indirect voting
Methods for dealing with uncertainty	– group of experts must reach consensus about subjective probabilities and pay-offs – uncertainties revealed explicitly during discussion	– experts with heterogeneous views vote, subsequent averaging reduces biases	– experts do not discuss pay-offs or probabilities but vote on policy recommendation
Examples	DA, BoE*, SR* (fan chart distribution is consensual)	DA	CNB, BoC, RBNZ* (BOGSAT)
Major pros	All information available to monetary policy makers. Biases in expert judgement are detected and reduced.	All information available to monetary policy makers. Biases in expert judgement are reduced by averaging.	The easiest option – it takes one short meeting to vote.
Major cons	Time consuming and sometimes frustrating.	Differences between expert opinions are not explained.	Policy makers have no priors about pay-offs and probabilities.

Note: Abbreviations: BoE – Bank of England, BoC – Bank of Canada, CNB – Czech National Bank, RBNZ – Reserve Bank of New Zealand, SR – Swedish Riksbank. DA – decision analysis
* In this case, the method has not been applied to the full extent (explanation given in brackets).

putting together the expert group may not be easy.[26] Also, there is a rule of thumb that each alternative should be able to get at least two or three votes. The composition of the group matters because the individual views are subject to biases.[27] The most common mistakes when assessing subjective probabilities are wishful thinking (the best outcome is attached the highest probability), experience bias (the alternative that was observed in the past is attached the highest probability) and overconfidence (neglecting that subjective probabilities can be wrong).

All the above-described tools employ methods to deal with these biases. Specifically, averaging of the individual opinions across the heterogeneous group of experts can be used in order to reduce biases. The averaging can be done by the experts or by a monetary policy maker who listens in on their debate. The latter method is sometimes referred to as the BOGSAT (bunch of guys sitting around talking) method. Alternatively the expert group can vote anonymously on a set of proposed subjective probabilities and then the group must discuss the outcome of this initial voting and agree on consensual probabilities. This method is called the Delphi method.[28] It is probably the most efficient method for reducing the biases, but it can be very time consuming. However, even simpler tools, such as averaging of the indi-

[26] The comment that putting together the expert group is not an easy task has been made by M. King. In the case of significant model uncertainty, researchers that have a deep knowledge of alternative models can help. In the case of data uncertainty, statisticians that analyse specific data in a very detailed way can improve the discussion.

[27] Clemen (1996) and Wright and Goodwin (1998) summarise possible biases that can affect the specifications of subjective probabilities.

[28] Armstrong (1985) explains the Delphi method, initially developed by the RAND Corporation in 1969 for technological forecasting, in more detail.

TABLE 6 Interest Rate Decision

	Board members reach consensus	Board members vote individually	Governor decides
Methods for dealing with uncertainty	– Policy makers have different information than experts. – Policy makers use consensus method to avoid biases.	– Policy makers have different information than experts. – Policy makers use averaging method by voting.	– Governor has different information than experts. – Governor speaks with advisors (BOGSAT).
Examples	DA (Delphi), BoC, BoE*, SR* (in both cases, there is an iterative debate about the distribution around the central forecast)	DA (heterogeneous group of experts), CNB, BoE*, SR*	DA, RBNZ
Major pros	Indirect revealing of pay-offs and probabilities to other decision makers and consensus are respected methods for dealing with uncertainty.	Fast	Fast and transparent
Major cons	Time consuming; Transparency lower since pay-offs and probabilities are not revealed.	If voting pattern not announced, transparency not so high. Outcome depends on who is present.	No additional method for dealing with uncertainty added

Note: Abbreviations: BoE – Bank of England, BoC – Bank of Canada, CNB – Czech National Bank, RBNZ – Reserve Bank of New Zealand, SR – Swedish Riksbank. DA – decision analysis. CMS – Cogley, Morozov and Sargent (2003), FD – Don (2001), HSYB – Hall, Salmon, Yates and Batini (1999), KW – Wallis (2004).

* In this case, the method has not been applied to the full extent (explanation given in brackets).

vidually attached probabilities, can still reduce a significant portion of the biases. It is worth noting that all these methods can be also employed by monetary policy makers in the second stage of the decision-making process.

2.4 The Interest Rate Decision

When deciding about interest rates, monetary policy makers use all the information presented to them by the experts, all the additional information they have, and their judgement and preferences in order to take the final decision about interest rates.[29] Their preferences better represent the preferences of society as a whole than do the preferences of the experts, owing to the democratic nomination process that ensures this is the case. Since they often have additional information, they can also have different views on the subjective probabilities. This implies that monetary policy makers can decide differently from the policy recommendation made by the experts. When deciding about interest rates, monetary policy makers employ similar methods for dealing with uncertainty to those used by the experts when they make decisions about the pay-offs and probabilities (*Table 6*).

[29] The role of monetary policy makers has recently been analysed in Goodhart (2003), King (2002), Lombardelli, Proudman and Talbot (2002) and Macklem (2002).

The system of voting by members of the decision-making body is respected as an important method for dealing with uncertainty, according to decision analysis, although the voting is rarely mentioned among the methods that inflation targeters claim to use for dealing with uncertainty. It is worth remembering that iterations, used to improve the forecast, can to some extent be a substitute for the consensus method. If several stages of the decision-making process are repeated and the monetary policy makers are part of the expert group, the central forecast can move closer to the best expected outcome.

There are trade-offs when designing the voting system of the decision-making body. The more the voting system helps in dealing with uncertainty, the less transparent it is for external observers. Specifically, if the Governor decides about monetary policy interest rates himself, observers can combine their knowledge of the published forecast with their guesses about the Governor's loss function and subjective probabilities. Subsequently, they can form their views about future policy actions more easily. If the decision-making body consists of several members who decide individually, external observers can only make guesses about the aggregated loss function and aggregated probabilities from the interest rate decision. If one member of the decision-making body is absent from the policy meeting, the aggregate loss function and the aggregate subjective probabilities that are behind the final decision are likely to change. In this case, publishing the votes improves the knowledge about the individual loss functions and subjective probabilities, which are more stable than aggregates and hence easier to predict. If the decision-making body makes consensual decisions, the individual loss functions and subjective probabilities are very difficult for external observers to extract. In this case, some additional information, such as an indication of the future policy bias, may be needed to improve external communication.

3. Lessons to Be Learnt from the Survey

Inflation targeters use a broader variety of methods than it seems at first sight. Although not all the methods are always worked with explicitly or described fully to the general public, inflation targeters do employ a broad variety of methods to deal with uncertainty when they set interest rates. Their repertoire ranges from stochastic simulations to working with subjective probabilities and pay-offs to considering the outcome of expert voting. In this respect, monetary policy makers are similar to decision makers leading important institutions in other areas. This conclusion corresponds to the claims made often by monetary policy makers that their decisions cannot be approximated with a model-based forecast or a model-based policy rule without substantial simplifications.

External communication does not explain all the methods systematically. It comes as a surprise that the variety of methods employed by inflation targeters is so large, because inflation targeters do not focus on communicating their methodologies systematically. They often describe the risks attached to the forecasts in order to communicate that the probability of hitting precisely the mid-point of the inflation target is not high.[30] The risks are described verbally or with the help of fan charts or alternative forecasts. Some inflation targeters also publish information about how the individual policy makers voted. The policy recommendations of the experts and the subjective probabilities attached to the alternative sets of assumptions or pay-offs are often treated implicitly. The implicit treatment of some elements of the methodology may be one of the reasons why the research still cannot approximate well how decisions about interest rates are taken.

Inflation targeters can learn from each other. Inflation targeters do not use the same methods to deal with uncertainty. Hence, they can compare notes and learn from each other. For example, the final decision is taken differently: by reaching a consensus among the board members, by iterative forecasting procedures, or by independent votes by individual members or by just one decision-maker. One can also observe a large variety of methods when the alternative sets of assumptions are specified. They are represented with the help of probability distributions, with variant forecasts (defined with respect to the central forecast) or with two boundary sets of assumptions that help to open the policy debate. The research should focus more on analyzing which methods yield better results. It is worth noting that the components of the decision-making process that are discussed externally more often are very similar in all five surveyed cases. Specifically, the central forecast is typically model-based and the model is used for producing alternative forecasts and policy simulations.

Inflation targeters can learn from economic research. The survey showed that inflation targeters have so far stayed in the middle ground as far as forecasting tools are concerned, while research papers have moved the technology frontier further. This is probably due to the fact that greater sophistication is costly in terms of know-how and the time required for the forecasting exercise, and even in terms of more complicated debate. The example of the CNB indicates that inflation targeters in emerging economies usually start with expert forecasts, and introduce fully model-based forecasts at a later stage. The economic research has recently offered powerful methods for dealing with certain types of uncertainties inside the model framework, such as Bayesian fan charts or the use of several models in parallel to produce the forecast. These should be gradually incorporated into the methods employed by inflation targeters to deal with uncertainty.

Inflation targeters can learn from decision analysis. While robust control and Bayesian techniques can help with the initial stages of the decision-making process, decision analysis can help improve the methods in the latter stages. Intuition and judgement are not incorporated into the decision-making process as formally as they are in the decision-analysis framework. Specifically, the experts often work with their subjective probabilities and pay-offs implicitly. Decision analysis suggests that a well-designed

[30] Issing (2002) and Budd (1998) stress that it is important to let the general public know that monetary policy cannot prevent all problems.

methodology for incorporating judgement and intuition, both necessary for attaching probabilities and pay-offs, can reduce biases substantially. Moreover, the experts' know-how can be fully utilized only if revealed to the monetary policy makers. For example, more attention should be paid to methods of constructing subjective probabilities. Instead of voting on the policy recommendation only, experts can systematically employ one of the earlier-mentioned methods, such as the Delphi method or averaging, to attach subjective probabilities to alternative sets of assumptions.

Not all methods are employed with the same frequency. The full forecasting round, including complete robustness analysis, is a time-consuming exercise, and, consequently, it is often the case that interest rates are changed more frequently than the inflation forecast. This implies that some of the methods for dealing with uncertainty are used more frequently than the ones incorporated into the central forecast. For example, the methods employed in order to attach subjective probabilities to alternative sets of assumptions can be employed prior to each interest rate decision without updating the alternative sets themselves. In extreme situations, monetary policy makers can decide about interest rates after employing the methods used during the actual decision meeting only. This may happen, for example, during times of financial or exchange-rate turbulence, when monetary policy makers can hold policy meetings very frequently and there is only time for intuitive decisions.[31]

[31] Smidkova et al. (1998) documents that policy meetings are very frequent in these circumstances.

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SUMMARY

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How Inflation Targeters (Can) Deal with Uncertainty

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The paper argues that a well-designed methodology for dealing with uncertainty improves the quality of interest-rate decisions taken by inflation targeters. A well-planned methodology is also more easily communicated to the general public, and the subsequent greater transparency makes inflation targeting more efficient. Therefore, it is relevant for an inflation targeter to consult with or consider information from other inflation targeters, researchers, and relevant decision makers when designing or improving upon their methodology. The paper also summarizes the results of a recent survey on methods for dealing with uncertainty for inflation targeters. The results are presented in a framework designed in line with decision analysis. The paper summarizes which methods are commonly used by inflation targeters and what lessons can be learnt from economic research and from decision makers.