Chapter 23
Country and Multi-Country Forecasting and Policy Models: From Statistical Tools to Structural Policy Frameworks

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Abstract This chapter reviews the historical evolution of macroeconomic forecasting and policy models, tracing the development from early large-scale macroeconometric systems to contemporary Forecasting and Policy Analysis Systems (FPAS) used in central banks, government authorities, and international institutions. Using the trade-off between empirical forecasting performance and theoretical consistency as a unifying theme, the chapter examines the roles of statistical and econometric models, DSGE frameworks, and semi-structural Quarterly Projection Models (QPMs) in modern policy analysis. Rather than focusing on individual methodologies in isolation, the chapter emphasizes how different modeling traditions evolved in response to the strengths and limitations of their predecessors. It highlights that some elements of earlier modeling paradigms proved more durable than others: large-scale macroeconometric systems proved vulnerable as structural policy models, yet their ambition to organize forecasting and policy analysis within coherent quantitative frameworks became a lasting institutional legacy. Statistical models retained their relevance in short-term forecasting and nowcasting, DSGE models reshaped structural interpretation and counterfactual policy analysis, and semi-structural models emerged as durable operational frameworks for forecast rounds and policy communication. The chapter concludes that the most important lesson from the history of macroeconomic modeling is not the emergence of a single dominant framework, but the development of integrated forecasting ecosystems in which statistical tools support short-term forecasting and nowcasting, semi-structural models typically serve as the core forecasting tool, and DSGE models provide structural interpretation and policy analysis. In this sense, FPAS represents the institutional synthesis of several decades of advances in macroeconometric modeling and policy analysis.[1]

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[1] The views expressed herein are those of the author and do not necessarily represent those of the International Monetary Fund.

23.1 Introduction: How Best-Practice Central Banks and Governmental Authorities Structure Their Forecasting and Policy Analysis (FPAS) Systems

Modern macroeconomic policy institutions operate in an environment characterized by uncertainty, incomplete information, and rapidly changing economic conditions. Monetary policy decisions, fiscal policy assessments, and macroeconomic surveillance require a coherent view of the economy's current state, its likely future evolution, and the consequences of alternative policy choices. Over the past several decades, central banks and international institutions have therefore moved away from relying on individual forecasting models toward integrated Forecasting and Policy Analysis Systems (FPAS), which combine models, data, expert judgment, and institutional processes into a unified decision-support framework (Berg et al., 2006; Berg & Portillo, 2018).

Importantly, FPAS is not a model in itself, but an institutional framework for organizing forecasting, policy analysis, and decision-making. While a core macroeconomic model typically occupies a central position within the system, its effectiveness depends equally on supporting elements such as data infrastructure, forecast-round procedures, model governance, scenario design, and communication practices. Forecasts are generated through an iterative process in which incoming data, external assumptions, model-based projections, and expert judgment are continuously reconciled and refined.

The emergence of Forecasting and Policy Analysis Systems (FPAS) reflects the broader historical evolution of macroeconomic policymaking over the past seven decades. During the post-war period, governments increasingly embraced active fiscal and monetary stabilization policies inspired by the Keynesian consensus, creating a growing demand for quantitative tools capable of supporting economic planning and policy decisions. This led to the development of large-scale macroeconometric systems such as the Klein-Goldberger model (Klein & Goldberger, 1955; Bodkin et al., 1991), the FRB-MIT-Penn model (De Leeuw & Gramlich, 1969), and later OECD INTERLINK (P. Richardson, 1987). These frameworks represented the first serious attempts to combine national accounts, economic theory, and econometric estimation within comprehensive forecasting and policy simulation frameworks. These pioneering models transformed macroeconomic policymaking by demonstrating that economic developments and alternative policy choices could be analyzed within internally consistent quantitative systems. Over time, however, concerns regarding parameter instability, the treatment of expectations, policy invariance, and vulnerability to structural change gradually reduced confidence in purely econometric structural systems, motivating the search for alternative modeling approaches.

The rational expectations revolution and the subsequent development of DSGE models addressed many of these theoretical shortcomings by introducing explicit microeconomic foundations and rational expectations. Yet practical experience revealed that fully structural models alone were often insufficient for operational forecasting. Statistical models frequently outperformed them in short-term forecasting exercises, while policymakers continued to require flexible tools capable of incorporating institutional knowledge and rapidly evolving economic conditions.

Modern FPAS frameworks emerged as a synthesis of these competing traditions. Rather than relying on a single methodology, policy institutions increasingly adopted suites of models that exploit the comparative advantages of different approaches. Statistical and econometric models contribute short-term forecasting accuracy and real-time signal extraction. Semi-structural models organize medium-term projections and policy scenarios. Structural models provide theoretical discipline, economic interpretation, and counterfactual analysis. Together, these tools form an integrated analytical framework that supports policy decisions under uncertainty.

This philosophy is reflected in the operational practices of many leading institutions. The Bank of Canada pioneered the development of the Quarterly Projection Model (QPM), one of the earliest examples of a semi-structural forecasting framework designed specifically for inflation-targeting central banks (Bank of Canada, 2015). The Reserve Bank of New Zealand subsequently developed a closely related FPAS architecture combining structured forecast rounds, model-based projections, and formal judgmental adjustments (Reserve Bank of New Zealand, 2018). The Czech National Bank later became one of the most inspiring examples of operational FPAS implementation in an inflation-targeting environment.

The International Monetary Fund played a particularly important role in disseminating FPAS frameworks globally through technical assistance, surveillance activities, and model development (Berg et al., 2006; Berg & Portillo, 2018). Within the Eurosystem, the European Central Bank and national central banks adopted similar suite-of-models approaches, combining statistical tools, semi-structural forecasting frameworks, and structural models to support policy analysis (K. Christoffel et al., 2008). Comparable practices can also be observed at the Bank of England and many other inflation-targeting central banks.

Despite institutional differences, these frameworks exhibit remarkable similarities. Most combine short-term forecasting tools, a medium-term semi-structural forecasting model, and one or more structural models used for interpretation and scenario analysis. In open economies, these frameworks often incorporate foreign demand, exchange-rate channels, commodity prices, and international financial conditions. Multi-country extensions naturally arise in institutions such as the IMF and ECB, where global spillovers and international transmission mechanisms are central to policy analysis.

Building on the preceding chapters on business-cycle measurement, DSGE modeling, and related econometric methods, this chapter shifts the focus from individual techniques to the institutional forecasting systems in which these tools are used together. Its objective is therefore not to reassess each model class in isolation, but to show how statistical, structural, and semi-structural approaches are combined in country and multi-country policy environments.

The remainder of the chapter traces the evolution of macroeconomic forecasting and policy models from both historical and operational perspectives. Section 23.2 examines the historical development of country and multi-country macroeconometric systems and introduces the trade-off between empirical fit and theoretical coherence as a conceptual framework for understanding different model classes. Section 23.3

reviews the statistical and econometric tools that continue to dominate short-term forecasting and nowcasting. Section 23.4 discusses the rise of DSGE models and their contribution to structural policy analysis. Section 23.5 examines semi-structural models and Quarterly Projection Models (QPMs), which have become the operational core of many contemporary FPAS frameworks. Section 23.6 concludes by arguing that the evolution of macroeconomic forecasting is best understood not as a succession of competing paradigms, but as a gradual movement toward integrated forecasting systems in which different models perform complementary roles within a broader policy framework.

23.2 Suites of Models and the Historical Evolution of FPAS: From Early Macroeconometric Systems to Modern Policy Frameworks

The evolution of modern macroeconomic forecasting frameworks reflects a broader development in macroeconomic modeling over the past seven decades. Throughout this period, economists and policy institutions have repeatedly confronted a fundamental challenge: how to balance empirical forecasting performance with theoretical consistency, policy relevance, and operational usability. Different generations of models approached this problem from different directions. Some emphasized statistical accuracy and robustness to changing data patterns; others prioritized economic interpretation, structural coherence, and counterfactual policy analysis. The history of macroeconomic modeling is therefore not simply a sequence of competing techniques, but a gradual process of institutional learning about what different types of models can and cannot do.

A useful concept for understanding this evolution is provided by the Pagan Diagram (Pagan, 2003). Rather than classifying models into rigid categories, Pagan characterizes macroeconomic models according to their position along two key dimensions: empirical fit and theoretical coherence. Models that prioritize empirical performance often achieve superior forecasting accuracy, especially at short horizons, but may provide limited economic interpretation. Conversely, models grounded in economic theory typically generate more coherent explanations of economic developments and policy transmission mechanisms, but may sacrifice forecasting performance, flexibility, or ease of implementation. Much of the history of macroeconomic modeling can therefore be interpreted as an attempt to navigate this trade-off.

Pagan's framework also provides a useful taxonomy of contemporary macroeconomic models. At one end of the spectrum lie purely statistical forecasting tools, including time-series models, vector autoregressions, and more recent machine-learning approaches, which emphasize empirical forecasting performance. At the opposite end are DSGE models, which prioritize theoretical consistency through explicit microeconomic foundations and forward-looking expectations. Between these extremes lie semi-structural models, which combine selected theoretical relationships with sufficient empirical flexibility to support operational forecasting and policy analysis. The historical evolution of policy modeling can largely be understood as movement along this spectrum rather than the emergence of entirely new paradigms.

Historically, the first generation of macroeconomic policy models emerged during the post-war period, when governments increasingly relied on active fiscal and monetary stabilization policies inspired by the Keynesian consensus. Policymakers required quantitative tools capable of organizing a rapidly expanding body of macroeconomic data into coherent forecasts and policy simulations. One of the earliest examples was the Klein-Goldberger model, which combined Keynesian economic theory with econometric estimation to construct one of the first empirically estimated models of the U.S. economy (Klein & Goldberger, 1955). In structural terms, the model can be understood as a simultaneous-equation Keynesian system, combining behavioral equations for consumption, investment, money demand, wages, and labor-market outcomes with accounting identities linking expenditure, income, prices, and employment. During the following decades, progressively larger systems were developed, including the FRB-MIT-Penn (FMP) model, a collaborative forecasting framework developed by the Federal Reserve, MIT, and the University of Pennsylvania that became one of the principal tools for U.S. monetary and fiscal policy analysis (de Leeuw & Gramlich, 1968). Similar efforts also emerged internationally. The OECD INTERLINK model extended this approach to multiple countries by linking national forecasting models through trade, exchange rates, and international demand, allowing policymakers to analyze the transmission of economic shocks across economies (P. Richardson, 1987).

These large-scale macroeconometric systems represented ambitious attempts to construct comprehensive empirical representations of national and global economies. Their primary objective was to provide policymakers with quantitative frameworks capable of producing internally consistent forecasts and evaluating alternative policy scenarios. In this respect, they marked a decisive institutional turning point. Macroeconomic policy was no longer supported only by isolated indicators, partial-equilibrium reasoning, or qualitative judgment. Instead, governments and central banks increasingly sought integrated quantitative systems capable of linking national accounts, behavioral relationships, policy instruments, and forecast assumptions within a common analytical framework.

These early systems achieved several important successes. They demonstrated that macroeconomic relationships could be estimated systematically using national accounts and econometric methods, introduced internally consistent projections across a large number of economic variables, and established a disciplined framework for scenario analysis and the quantitative evaluation of alternative policy choices (Bodkin et al., 1991; Fromm & Taubman, 1968; Green et al., 1972). In many respects, they laid the foundations of modern forecasting practice by showing that macroeconomic policy could be supported by formal model-based systems rather than fragmented empirical evidence. Their most durable contribution was therefore not any specific equation or model platform, but the institutional idea that forecasting and policy analysis should be organized within a coherent quantitative framework.

The historical lesson was therefore not that early macroeconometric systems failed without consequence. Rather, some elements of that tradition proved durable, while others lost credibility over time. The attempt to use a single historically estimated system simultaneously as a forecasting device, a structural representation of the economy, and a tool for policy counterfactuals proved too ambitious after the Lucas critique and the rational expectations revolution. By contrast, the institutional ambition behind these systems—the organization of data, forecasts, policy instruments, assumptions, and alternative scenarios within a common quantitative framework—became a lasting contribution to macroeconomic policy practice.

At the same time, the limitations of the early large-scale systems gradually became apparent. Parameter instability, difficulties in modeling expectations, and sensitivity to structural change reduced forecasting reliability, particularly during periods of economic turbulence. Many behavioral equations relied on ad hoc specifications that lacked clear theoretical foundations, making policy simulations difficult to interpret. These concerns became particularly prominent following the Lucas critique (Lucas, 1976) and the broader rational expectations revolution, which challenged the validity of policy evaluations based on historically estimated behavioral relationships.

This realization stimulated the diversification of macroeconometric modeling. Statistical methods, including time-series models, vector autoregressions, and later Bayesian forecasting techniques, gained prominence because of their strong empirical forecasting performance and robustness to structural change. At the same time, DSGE models emerged as a theoretically coherent alternative based on forward-looking expectations, optimization behavior, and explicit policy transmission mechanisms. Each approach addressed an important weakness of earlier macroeconometric systems, but neither proved to be a complete solution. Statistical models often lacked structural interpretation for policy analysis, whereas DSGE models frequently remained too restrictive and data-intensive for operational forecasting. The subsequent development of semi-structural models can therefore be viewed as an attempt to reconcile these competing traditions by combining key theoretical relationships with empirically motivated dynamics.

The weakening of confidence in large-scale national systems did not end the search for model-based policy frameworks, but it changed the direction of that search. One important strand of this evolution extended the same logic beyond the national economy. The collapse of the Bretton Woods system, the oil crises of the 1970s, and the rapid expansion of international trade highlighted the growing importance of cross-border spillovers. Beginning in the 1970s, Project LINK and the OECD's INTERLINK model sought to connect national econometric models into cooperative global forecasting systems (Klein, 1976; P. Richardson, 1987). The IMF subsequently developed MULTIMOD and later the Global Economy Model (GEM), which provided multi-region frameworks for analyzing international transmission, policy scenarios, and global spillovers (Masson et al., 1990; Bayoumi et al., 2004; Pesenti, 2008). Other widely used global forecasting and simulation systems included the Federal Reserve Board's FRB/GLOBAL model and the National Institute Global Econometric Model (NiGEM) (Levin et al., 1997; Hantzsche et al., 2018). These frameworks extended the logic of national macroeconometric systems to the international economy by linking country models through trade flows, exchange rates, commodity prices, financial conditions, and external demand.

Successive generations of multicountry models gradually incorporated richer trade linkages, financial transmission channels, commodity markets, policy interactions, and eventually forward-looking expectations. More recent frameworks, including GIMF, FSGM, ECB multicountry models, and the Global Projection Model (GPM) family, further integrated the insights of DSGE and semi-structural modeling traditions into multicountry policy analysis. Across these successive generations, the objective remained remarkably consistent: to provide policymakers with internally coherent frameworks capable of interpreting international economic developments, analyzing global shocks, and evaluating coordinated policy responses in an increasingly interconnected world economy.

These multicountry systems highlighted both the promise and complexity of international macroeconomic modeling. They demonstrated the importance of cross-country spillovers and the need for internationally consistent forecasts, while also revealing the practical challenges associated with data harmonization, model maintenance, and the coordination of assumptions across countries. Over time, the specific architectures of these models often became less important than the institutional lesson they conveyed: domestic forecasts cannot be constructed in isolation from the global environment. This principle has become even more relevant as global financial conditions, commodity-price shocks, supply-chain disruptions, and international policy spillovers increasingly shape domestic macroeconomic outcomes.

The historical evolution of macroeconomic modeling therefore does not point toward a universally superior framework. Its broader lesson is that the ambition to build a single comprehensive model of the economy gradually gave way to a more pragmatic institutional logic. Early macroeconometric systems initiated the search for coherent model-based policy frameworks by showing that forecasts, assumptions, scenarios, and policy analysis could be organized within an internally consistent quantitative structure. Later modeling traditions revised the technical foundations of that structure, but preserved the underlying objective of disciplined, transparent, and internally coherent policy analysis. Modern policy institutions increasingly rely on suites of complementary models not because this arrangement is theoretically elegant, but because different policy questions require different forms of empirical evidence, structural interpretation, operational flexibility, and expert judgment. The following sections examine how these roles became institutionalized in contemporary Forecasting and Policy Analysis Systems, beginning with the statistical and econometric methods that continue to provide the empirical foundation for short-term forecasting.

23.3 Purely Statistical and Econometric Models for Nowcasting and Near-Term Forecasting

The historical reassessment of large-scale macroeconometric systems did not imply that statistical and econometric methods lost their relevance for macroeconomic policy. On the contrary, one of the clearest lessons from the evolution of macroeconomic forecasting is that the usefulness of econometric models depends critically on the task they are asked to perform. The early large-scale systems proved less durable as comprehensive structural representations of the economy or as reliable tools for policy counterfactuals. However, many of the statistical and time-series methods that developed alongside and after them remained highly effective when used for a more modest but essential purpose: extracting information from data and producing reliable near-term forecasts.

This distinction is central to understanding why purely statistical and econometric forecasting models remained a permanent feature of policy institutions. The Lucas critique and the rational expectations revolution challenged the use of historically estimated behavioral equations for policy evaluation, but they did not eliminate the need to measure current economic conditions, detect turning points, and forecast the near-term evolution of output, inflation, employment, trade, or financial variables. Policy institutions still needed tools capable of processing incoming data quickly and systematically. Statistical models therefore retained their importance not because they solved the problem of structural policy analysis, but because they proved highly effective at a task that never disappeared: short-term forecasting and nowcasting.

The origins of modern statistical forecasting can be traced to the development of classical econometric methods during the twentieth century. Rather than attempting to construct comprehensive representations of the entire economy, many empirical approaches focused on extracting robust relationships from macroeconomic data. Regression-based forecasting models were gradually complemented by error-correction models and cointegration techniques, allowing economists to distinguish between long-run equilibrium relationships and short-run dynamics. The contributions of Engle & Granger (1987) and Johansen (1988) significantly expanded the empirical toolkit available to policymakers by providing statistically coherent methods for modeling non-stationary macroeconomic time series.

Over time, the institutional role of these methods became more specialized. As macroeconomic theory increasingly emphasized optimization, expectations, and general equilibrium during the 1980s and 1990s, statistical models gradually moved away from serving as comprehensive policy models. Instead, they became tools designed to maximize the information extracted from available data and to deliver accurate short-term projections. Their comparative advantage increasingly lay in empirical forecasting rather than structural interpretation. This specialization was not a weakness. It was precisely what allowed statistical models to remain useful even as broader macroeconomic theory moved in different directions.

Perhaps the most important turning point came with Sims' critique of traditional structural econometric systems and the introduction of vector autoregressions (VARs) (Sims, 1980). Rather than imposing extensive theoretical restrictions before estimation, VARs allowed the dynamic relationships among macroeconomic variables to emerge more directly from the data. This represented a fundamental change in modeling philosophy. The objective was no longer to construct a complete structural representation of the economy within a single large system, but to exploit the information contained in observed time series as efficiently as possible. Subsequent developments, including Bayesian VARs (BVARs), factor-augmented VARs

(FAVARs), and structural identification techniques, further expanded the empirical toolkit available to policymakers (Bańbura et al., 2010; O. J. Blanchard & Quah, 1989; Uhlig, 2005; Kilian & Lütkepohl, 2017).

These approaches proved successful because they addressed several weaknesses of earlier macroeconometric systems. They were generally easier to estimate, more robust to specification errors, and often delivered superior short-horizon forecasting performance. At the same time, they remained flexible enough to incorporate foreign variables, commodity prices, financial indicators, survey information, and other sources of information relevant for increasingly open and globally integrated economies. In operational settings, these models could be updated frequently, compared against alternative specifications, and used as benchmarks for forecast rounds. As a result, VAR-, BVAR-, FAVAR-, and VECM-based systems continue to serve as important empirical forecasting tools in many central banks and policy institutions.

Another important stage in this historical evolution was driven by the rapid expansion of available data. The increasing availability of high-frequency and large-dimensional datasets stimulated the development of mixed-frequency methods such as MIDAS regressions, which enabled policymakers to combine quarterly national accounts with monthly, weekly, or even daily indicators (Ghysels et al., 2004; Clements & Galvão, 2008; Foroni et al., 2015). These methods were particularly valuable because many key policy variables, such as GDP, are observed with delay and subject to revision, while other indicators, including labor-market data, surveys, financial prices, tax receipts, or trade statistics, arrive more frequently. Mixed-frequency models therefore helped bridge the gap between the information policymakers need in real time and the slower rhythm of official macroeconomic data releases.

More recently, machine-learning algorithms and data-rich forecasting systems have further expanded the ability of institutions to process large volumes of information and improve nowcasting performance (Goulet Coulombe et al., 2022; Medeiros et al., 2021; A. Richardson et al., 2021). Although these methods differ substantially from classical time-series models in their statistical foundations, they share a similar institutional function: extracting predictive signals from large and heterogeneous datasets. Their growing use reflects the same historical lesson that motivated earlier statistical forecasting tools. When the objective is to measure the current state of the economy or forecast the next few quarters, empirical flexibility and data processing capacity may be more valuable than a fully articulated structural theory.

From a historical perspective, what is most remarkable is not how much statistical forecasting techniques have changed, but how consistently their institutional function has remained relevant. Their methodology evolved from simple regressions and bridge equations to cointegration models, VARs, Bayesian estimation, mixed-frequency models, factor models, and machine-learning algorithms. Yet their role within policy institutions changed much less dramatically. Throughout successive generations of macroeconomic modeling, they continued to provide policymakers with timely empirical information about current economic conditions and near-term developments.

The durability of statistical and econometric forecasting models therefore reflects their functional specialization within policy institutions. Their continued relevance does not stem from an ability to provide comprehensive structural interpretations of the economy, but from their effectiveness in addressing a narrower set of empirical tasks. They help policymakers assess the current state of economic activity, detect turning points, evaluate the persistence of inflationary pressures, monitor the transmission of external shocks, and compare incoming data with baseline projections. These functions are central to real-time policy analysis. The timely interpretation of new information is a necessary input into any broader forecasting process, scenario exercise, or policy discussion.

At the same time, history also revealed the limits of purely statistical models. Because they are designed to capture empirical regularities rather than structural economic mechanisms, they offer limited guidance regarding policy counterfactuals, welfare analysis, or the transmission of economic shocks under alternative regimes. They may describe and forecast economic developments remarkably well, but they generally cannot explain how alternative policy choices would alter future outcomes in a structurally coherent way. A VAR may summarize dynamic correlations among interest rates, inflation, output, and exchange rates, but by itself it cannot fully answer how the economy would behave under a different monetary policy rule, a new fiscal regime, or a structural reform.

The lesson is therefore not that statistical models displaced structural analysis, nor that the Lucas critique made econometrics irrelevant. Rather, it clarified the conditions under which econometric tools are most useful in policy institutions. Statistical and time-series models remained indispensable because they provided disciplined methods for extracting signals from incoming data, assessing short-term dynamics, benchmarking forecasts, and detecting turning points in real time. Their limitations became apparent only when they were asked to perform the broader structural role once assigned to large-scale macroeconometric systems. The historical contribution of this tradition therefore lies in its transformation from a candidate foundation for comprehensive policy models into a specialized empirical infrastructure for modern forecasting practice.

23.4 Applied DSGE Models in Central Bank FPAS Frameworks

The emergence of Dynamic Stochastic General Equilibrium (DSGE) models marked a major turning point in the history of macroeconometric modeling. Their significance lies not simply in the introduction of a new model class, but in the way they responded to a deeper crisis in macroeconomic policy analysis. The large-scale macroeconometric systems of the post-war period had created the ambition of organizing forecasts, policy simulations, and macroeconomic scenarios within coherent quantitative frameworks. This ambition remained central to policy institutions, even as the specific behavioral equations and historically estimated structures of many early models became increasingly difficult to defend. By the late 1970s and early 1980s, confidence in these systems had weakened considerably as parameter instability, ad hoc expectation formation, and sensitivity to policy-regime changes became increasingly difficult to ignore.

The Lucas critique gave this dissatisfaction its most influential theoretical formulation. If the estimated relationships in macroeconometric models were not invariant to policy changes, then forecasts and policy simulations based on historical correlations could be misleading (Lucas, 1976). The rational expectations revolution reinforced this point by emphasizing that economic agents form expectations about future policy and adjust their behavior accordingly. These arguments did not make econometrics irrelevant; rather, they clarified the limits of using reduced-form historical relationships for structural policy counterfactuals. The challenge was to preserve the ambition of coherent model-based policy analysis while rebuilding its foundations around expectations, incentives, and policy regimes.

The first systematic response came from the Real Business Cycle (RBC) literature, especially the work of Kydland & Prescott (1982). RBC models provided the methodological architecture that later DSGE models would inherit: intertemporal optimization, equilibrium dynamics, stochastic shocks, and explicit assumptions about preferences, technologies, and constraints. In contrast to earlier macroeconometric systems, the objective was not to estimate large numbers of behavioral equations separately, but to derive aggregate macroeconomic relationships from a unified model of optimizing agents operating under uncertainty. Households make intertemporal decisions regarding consumption, saving, and labor supply; firms choose production, investment, and pricing strategies subject to technological and market constraints; and governments and central banks implement fiscal and monetary policies according to explicit policy rules. The interaction of these decisions determines equilibrium outcomes in goods, labor, financial, and external markets (Kydland & Prescott, 1982; Clarida et al., 1999; Woodford, 2003; Gali, 2015). This represented a decisive shift in the history of macroeconomic modeling: the organizing principle moved from fitting historical correlations to specifying structural mechanisms through which policy affects the economy both directly and through expectations about future policy and future economic conditions.

Early RBC models were deliberately stylized and often too frictionless for many policy applications, especially monetary policy. Their lasting importance was therefore methodological rather than empirical. They established the discipline of dynamic general-equilibrium modeling, but they did not yet provide a realistic framework for analyzing inflation, nominal rigidities, central-bank reaction functions, or short-run stabilization policy. The subsequent New Keynesian DSGE literature filled this gap by combining the RBC methodological apparatus with nominal and real frictions. Models with monopolistic competition, Calvo-type price and wage setting, and monetary-policy rules made it possible to analyze monetary transmission within an internally coherent dynamic framework (Clarida et al., 1999; Woodford, 2003; Gali, 2015).

In this sense, DSGE models represented both a continuation of earlier structural ambitions in macroeconometrics and a methodological break from the large-scale reduced-form systems that preceded them. They preserved the objective of linking forecasts, policy instruments, and macroeconomic outcomes within a unified analytical structure, but changed the foundations on which that structure rested. Instead of relying primarily on historically estimated behavioral equations, DSGE models derived aggregate relationships from assumptions about household optimization, firm behavior, market structure, policy rules, and equilibrium conditions (Kydland & Prescott, 1982; King et al., 1988; Clarida et al., 1999; Woodford, 2003). This placed expectations, policy regimes, and equilibrium restrictions at the center of macroeconomic policy analysis (Lucas, 1976; Woodford, 2003; Fernandez-Villaverde & Rubio-Ramirez, 2004).

Modern policy DSGE models differ substantially from the frictionless benchmark economies that characterized early theoretical contributions. Practical policy analysis requires models capable not only of generating persistence and inertia, but also of reproducing the richer transmission mechanisms observed in actual economies. As a result, contemporary DSGE frameworks incorporate a wide range of nominal, real, and financial frictions, including financial accelerator mechanisms, nominal price and wage indexation, habit formation in consumption, investment adjustment costs, variable capital utilization, and rule-of-thumb or liquidity-constrained households. Many applied models also depart from purely forward-looking expectations by allowing for hybrid or adaptive components, helping them generate more realistic inflation, wage, consumption, and investment dynamics. Influential contributions such as Christiano et al. (2005) and Smets & Wouters (2007) demonstrated that these mechanisms could significantly improve the empirical performance and policy relevance of DSGE models while preserving their general-equilibrium foundations.

The historical development of DSGE models also illustrates the gradual convergence between macroeconomic theory and econometric practice. The early RBC tradition relied heavily on calibration, using external evidence, steady-state ratios, and long-run empirical regularities to assign values to structural parameters (Cooley, 1995; King & Rebelo, 1999). This reflected both methodological conviction and practical necessity: many parameters were difficult to estimate reliably from aggregate time-series data, and the purpose of early models was often to discipline theoretical mechanisms rather than maximize statistical fit.

Over time, however, advances in computation and econometric methods changed the empirical status of DSGE modeling. Likelihood-based estimation became increasingly feasible, and Bayesian methods provided a natural framework for combining theory, prior information, and observed macroeconomic data (An & Schorfheide, 2007; Fernandez-Villaverde & Rubio-Ramirez, 2004). This development was historically important because it brought DSGE models closer to the econometric tradition they had initially challenged. Bayesian estimation did not eliminate calibration or judgment, but it made the interaction between theory and data more explicit. Priors encoded theoretical restrictions or external evidence, while the likelihood disciplined the model using observed macroeconomic dynamics.

Alternative estimation strategies also played an important role in this convergence. Simulated Method of Moments (SMM) and related simulation-based techniques estimate parameters by matching moments generated by the model to those observed in the data, thereby avoiding direct likelihood evaluation (Lee & Ingram, 1991; Duffie & Singleton, 1993). Other approaches focus on matching impulse responses from empirical VARs with those generated by the DSGE model or rely on indirect inference. These methods provide flexible alternatives when researchers wish to emphasize specific transmission mechanisms or avoid computationally intensive likelihood estimation (Rotemberg & Woodford, 1997; Christiano et al., 2005; Del Negro & Schorfheide, 2004; Smith, 1993).

The empirical implementation of DSGE models therefore evolved into a pragmatic mixture of calibration, estimation, and judgment. In principle, the objective is to identify parameter values that allow the model to reproduce the joint behavior of key macroeconomic variables while remaining consistent with economic theory. In practice, policy institutions rarely estimate every structural parameter simultaneously. Some parameters, particularly those governing steady-state relationships, are calibrated using microeconomic evidence, historical averages, institutional knowledge, or previous empirical studies. Others, especially those affecting dynamic adjustment, are estimated from the data. Estimation and calibration are therefore best viewed as complementary rather than competing methodologies. Each contributes to the empirical implementation of structural models according to the purpose of the analysis, the availability of data, and the institutional context in which the model is used.

By the early 2000s, this convergence of macroeconomic theory, computational methods, and econometric estimation helped establish DSGE models as the dominant structural framework in both academia and policy institutions (Smets & Wouters, 2003; An & Schorfheide, 2007; Del Negro & Schorfheide, 2013). The DSGE revolution thus did not simply replace econometrics with theory. Rather, it changed the terms on which macroeconometric models were built and evaluated. Econometric methods increasingly became tools for estimating, validating, disciplining, and comparing theoretically structured models, while macroeconomic theory provided the restrictions needed to interpret policy experiments and counterfactual simulations.

The growing maturity of DSGE methodology facilitated its adoption by central banks. Institutions such as the Czech National Bank, Sveriges Riksbank, Norges Bank, and Banco de la República incorporated DSGE-based frameworks into the preparation of policy forecasts and inflation reports (Andrle et al., 2009; Adolfson et al., 2007; Brubakk et al., 2006; Gonzalez et al., 2011). Major central banks developed their own institution-specific models: the European Central Bank introduced the New Area-Wide Model (NAWM) for monetary policy analysis in the euro area (K. P. Christoffel et al., 2008); the Federal Reserve developed frameworks such as EDO and the multicountry SIGMA model to analyze domestic policy and international spillovers (Erceg et al., 2006; Edge et al., 2009); and the Bank of Canada introduced ToTEM as a core structural tool for policy analysis. These experiences showed that DSGE models could be adapted to operational forecasting environments while maintaining consistency with monetary policy objectives, expectations formation, and the broader transmission mechanism.

At the international level, the IMF extended the DSGE tradition into a global setting through the development of multicountry frameworks such as the Global Integrated Monetary and Fiscal Model (GIMF) (Kumhof et al., 2010). Unlike traditional country models, GIMF explicitly incorporates international spillovers, fiscal interactions, and coordinated policy analysis across multiple regions. These developments demonstrated that DSGE models could serve not only as country-specific policy tools, but also as platforms for analyzing global macroeconomic interactions.

The widespread adoption of DSGE models generated a substantial body of practical experience. Policymakers valued their theoretical coherence and their ability to organize economic narratives, but day-to-day forecasting and policy work also revealed important operational challenges. These limitations did not invalidate the DSGE approach. Instead, they reshaped the understanding of its comparative advantage. Over time, DSGE models came to be viewed less as universal forecasting engines and more as structural frameworks that complement statistical, semi-structural, and judgment-based approaches within broader forecasting and policy analysis systems (Edge & Gurkaynak, 2010; Wieland & Wolters, 2013; Del Negro & Schorfheide, 2013).

This historical reassessment became especially important after the Global Financial Crisis. Many pre-crisis DSGE models had limited financial sectors, relied heavily on linear approximations around a stable steady state, and were poorly suited to capturing nonlinearities, rare events, balance-sheet disruptions, and regime shifts. The crisis therefore exposed the limits of theoretical coherence when key transmission mechanisms were omitted or underdeveloped (Caballero, 2010; Chari et al., 2009; O. Blanchard, 2018). In retrospect, the historical record suggests a more differentiated evaluation of the DSGE revolution. DSGE models did not replace empirical forecasting models, nor did they become universal short-term forecasting engines. Yet several of their core contributions proved remarkably durable: the emphasis on internal consistency, forward-looking expectations, structural interpretation, policy counterfactuals, and the disciplined treatment of policy regimes continues to shape modern macroeconometric practice. The post-GFC experience therefore shifted the evaluation of DSGE models away from the question of whether they could provide a complete representation of the economy and toward the more practical question of which mechanisms must be included for policy analysis to remain credible. Financial frictions, occasionally binding constraints, nonlinear dynamics, heterogeneity, and regime changes became central concerns in the next generation of structural policy models.

The post-crisis debate also revealed a historical echo in the criticism of macroeconomic models. Many concerns directed at DSGE models resembled earlier criticisms of large-scale macroeconometric systems. In both cases, technically sophisticated models were criticized for being difficult to interpret, sensitive to maintained assumptions, and insufficiently transparent about the role of judgment. The object of criticism changed: early macroeconometric models were often viewed as empirically elaborate systems with weak structural foundations, whereas DSGE models were criticized for combining strong theoretical discipline with missing or underdeveloped transmission mechanisms. Yet the underlying policy concern was similar. Models could provide discipline and consistency, but they could also create a false sense of precision if their assumptions, limitations, and judgmental elements were not made explicit.

Another important lesson concerned identification. Many economically meaningful concepts embedded in DSGE models, such as potential output, natural interest rates, preference parameters, or trend productivity growth, cannot be directly observed in the data. Empirical implementation therefore often faces weak identification, particularly when several parameters affect model dynamics in similar ways or when available macroeconomic data provide limited information about specific structural mechanisms (Canova, 2007; Canova & Sala, 2009; Iskrev, 2010; An & Schorfheide, 2007). In practice, this frequently requires combining estimation with calibration, auxiliary assumptions, and external evidence, reinforcing the complementary role of econometric methods and economic judgment.

Model behavior is also highly sensitive to assumptions regarding expectations formation and policy rules. One of the enduring insights inherited from the rational expectations revolution is that policy outcomes depend not only on current policy decisions, but also on how private agents anticipate future policy actions (Lucas, 1976; Taylor, 1993; Clarida et al., 1999). Whether monetary policy is represented by an inflation-targeting rule, an exchange-rate peg, or another policy regime can substantially alter model dynamics and policy conclusions. This sensitivity is not merely a technical feature of DSGE models; it reflects their central purpose as frameworks for studying how policy regimes shape private behavior and aggregate outcomes.

The practical implementation of DSGE models further requires careful calibration of the steady state. Following the tradition established by the real business cycle literature, many long-run relationships and structural parameters are calibrated using external evidence rather than estimated directly from the data (Cooley, 1995; King & Rebelo, 1999). Solving for the steady state often involves large systems of nonlinear equations and, in more complex applications, numerical methods such as homotopy algorithms (Judd, 1998; Miranda & Fackler, 2002). Multiple steady-state equilibria may exist, introducing an additional source of uncertainty into model calibration and policy analysis.

The combined challenges of identification, calibration, steady-state specification, and sensitivity to modeling assumptions help explain why DSGE models have generally been more successful as tools for structural interpretation and policy analysis than as stand-alone short-term forecasting devices. Comparative forecast evaluations frequently find that their greatest strength lies in organizing economic narratives, identifying structural shocks, and evaluating counterfactual policy scenarios, whereas more flexible statistical approaches often retain an advantage in near-term prediction, particularly during periods of structural change or heightened uncertainty (Edge & Gurkaynak, 2010; Wieland & Wolters, 2013; Del Negro & Schorfheide, 2013). From a historical perspective, this reassessment of the appropriate role of DSGE models represents one of the most important institutional lessons of the past two decades.

As DSGE models became increasingly integrated into policy institutions, attention gradually shifted from point forecasts toward the analytical outputs they generate for policy analysis. These include historical shock decompositions, counterfactual simulations, alternative policy-rule experiments, and welfare-based assessments of policy choices. Shock decompositions allow policymakers to attribute observed fluctuations to underlying demand, supply, financial, or policy disturbances. Counterfactual simulations help evaluate how the economy might have evolved under alternative policy actions or external conditions. Welfare analysis extends these capabilities by providing explicit criteria for assessing policy trade-offs within a coherent general-equilibrium framework.

The practical relevance of DSGE models is therefore best illustrated through their policy applications. At the IMF, multicountry DSGE frameworks such as GIMF have been used extensively to analyze fiscal consolidations, public investment programs, structural reforms, commodity-price shocks, and international spillovers (Kumhof et al., 2010; Anderson et al., 2013). Results from GIMF simulations have informed analytical chapters of the *World Economic Outlook* and other IMF flagship publications, providing a coherent framework for assessing the medium-term consequences of alternative policy choices and cross-country interactions.

Within the European policy environment, DSGE models have also played an important role in evaluating structural reforms. The European Commission's QUEST model became one of the most widely used frameworks for assessing the macroeconomic effects of labor-market reforms, product-market liberalization, fiscal consolidation strategies, demographic change, and investment programs (Roeger & in 't Veld, 2008; in 't Veld, 2015). Because QUEST explicitly links policy interventions to long-run growth, competitiveness, and public finances, it has been extensively employed in impact assessments and policy evaluations throughout the European Union.

Central banks have similarly relied on DSGE models to analyze monetary transmission and policy trade-offs. The ECB's New Area-Wide Model has been used to study the effects of monetary policy shocks, external demand disturbances, oil-price fluctuations, and international spillovers within the euro area (K. P. Christoffel et al., 2008; Coenen et al., 2018). At the Federal Reserve, frameworks such as SIGMA and EDO have been applied to examine the transmission of monetary policy, exchange-rate movements, and global shocks to the U.S. economy (Erceg et al., 2006; Edge et al., 2009). In these applications, the principal value of DSGE models lies not only in forecasting, but also in providing a theoretically coherent environment for policy experiments that cannot be directly observed in historical data.

These examples highlight an important distinction between forecasting and policy analysis. Statistical and semi-structural models often play the leading role in producing baseline projections, especially at short horizons. DSGE models, by contrast, are particularly valuable when policymakers need to answer counterfactual questions. How would inflation have evolved under a different monetary policy rule? What are the medium-term consequences of a fiscal expansion? How large are the international spillovers from structural reforms in a major economy? Questions of this type require a framework capable of linking policy interventions, expectations, and economic outcomes within a coherent general-equilibrium setting. At the same time, the experience of institutions such as the Czech National Bank, Sveriges Riksbank, Norges Bank, and Banco de la República demonstrates that DSGE-based frameworks can also play a central role in forecasting systems when appropriately adapted to the operational requirements of monetary policy (Adolfson et al., 2007; Brubakk et al., 2006; Andrle et al., 2009; Gonzalez et al., 2011).

The evolution of DSGE models thus illustrates a broader pattern in the history of econometrics. New modeling frameworks rarely eliminate their predecessors; rather, their most durable contributions are absorbed into a wider toolkit. DSGE models did not make VARs, semi-structural models, judgmental forecasting, or satellite models obsolete. Instead, they changed the standards by which macroeconometric models were evaluated. After the DSGE revolution, policy models were expected to be clearer about expectations, policy regimes, structural shocks, and counterfactual interpretation. At the same time, the empirical implementation of DSGE models increasingly relied on the econometric methods and diagnostic tools that had developed alongside the broader forecasting literature.

This historical evolution laid much of the foundation for modern Forecasting and Policy Analysis Systems (FPAS). DSGE models did not become comprehensive forecasting engines, nor did they resolve all the operational problems that had motivated their development. Their lasting contribution was more specific: they reintroduced theoretical discipline into applied macroeconometric modeling, placed expectations and policy regimes at the center of policy analysis, and provided a structured language for counterfactual experiments. In an FPAS environment, DSGE models therefore serve primarily as structural anchors within a broader modeling infrastructure that may also include semi-structural gap models, VARs, near-term forecasting tools, satellite equations, expert judgment, and scenario-analysis frameworks (Berg & Portillo, 2018). Their role is to discipline forecasts and scenarios through explicit assumptions about behavior, expectations, shocks, and policy regimes, while other tools provide the empirical flexibility, short-term forecasting accuracy, institutional detail, and operational transparency required for regular forecast production. DSGE models thus represent less the final stage of macroeconometric evolution than an essential component of the modern suite-of-models approach.

23.5 Semi-Structural Models: The Practical Compromise for Forecasting and Policy Analysis

The rise of semi-structural models was the outcome of institutional learning from the practical limitations of both statistical forecasting systems and DSGE models. By the early 2000s, many central banks had reached a similar conclusion. Purely statistical models provided valuable information about current economic conditions and often delivered superior short-term forecasting performance, but they offered limited guidance for policy analysis (Lütkepohl, 2005; Hamilton, 1994; Bańbura et al., 2010). DSGE models, by contrast, generated internally consistent economic narratives and theoretically coherent policy simulations, but frequently proved too rigid, data-intensive, and operationally demanding for real-time forecasting environments (Chari et al., 2009; Caballero, 2010; O. Blanchard, 2018). These challenges were especially pronounced in emerging-market and low-income economies, where shorter data samples, frequent structural breaks, regime changes, and rapidly evolving institutional environments limited the empirical reliability and operational feasibility of fully specified DSGE frameworks (Berg et al., 2006; Berg & Portillo, 2018).

From a historical perspective, the development of Quarterly Projection Models (QPMs) marked a pragmatic turning point in modern macroeconometric modeling. Rather than seeking to resolve the tension between statistical accuracy and theoretical structure through a single dominant model, QPMs offered a practical compromise. The pioneering work of the Bank of Canada during the 1990s demonstrated that a relatively small macroeconomic model could support inflation-targeting policy decisions without imposing the full complexity of a DSGE framework (Black et al., 1994; Coletti et al., 1996). As inflation-targeting regimes spread across advanced and emerging-market economies, similar frameworks were gradually adopted by a growing number of central banks, transforming semi-structural modeling from an institutional innovation into a broadly accepted policy paradigm (Berg et al., 2006; Berg & Portillo, 2018).

The appeal of semi-structural models stemmed from their ability to translate the key economic insights of DSGE models into a form suitable for operational forecasting and policy analysis. Modern QPMs can therefore be viewed as reduced-form descendants of New Keynesian DSGE frameworks. They preserve many of the transmission mechanisms emphasized by DSGE models, including forward-looking expectations, monetary-policy reaction functions, nominal rigidities, and open-economy channels, but replace much of the underlying microeconomic structure with more flexible empirical relationships (Clarida et al., 1999; Woodford, 2003; Gali, 2015; Berg et al., 2006). This simplification made the models easier to estimate, calibrate, communicate, and adapt to changing economic conditions, while retaining the economic intuition required for policy analysis.

Most QPMs organize macroeconomic dynamics around four interconnected blocks: aggregate demand, inflation, monetary policy, and the external sector (Black et al., 1994; Coletti et al., 1996; Berg et al., 2006; Berg & Portillo, 2018). The aggregate demand block describes how monetary conditions, financial variables, and expectations influence spending decisions and the output gap, providing a reduced-form counterpart to the intertemporal consumption and investment decisions emphasized in New Keynesian DSGE models. The inflation block links inflation developments to demand pressures, inflation expectations, and external price shocks, typically combining forward-looking and backward-looking elements to capture both New Keynesian mechanisms and the inflation persistence observed in practice. The monetary policy block summarizes the behavior of the central bank, most often through an interest-rate reaction function in inflation-targeting regimes, but it can also represent exchange-rate pegs, managed exchange-rate arrangements, or hybrid monetary frameworks (Taylor, 1993; Clarida et al., 1999; Laxton et al., 2009). Finally, the external sector connects the domestic economy to the rest of the world through foreign demand, commodity prices, global financial conditions, capital flows, and exchange-rate dynamics, providing the basis for analyzing international spillovers and cross-country transmission mechanisms in multicountry applications (Berg et al., 2006; Carabenciov et al., 2013; Anderson et al., 2013).

Together, these building blocks provide a transparent representation of the main transmission channels relevant for monetary policy analysis. Their strength lies not in deriving every relationship from explicit optimization problems, but in imposing enough economic structure to support coherent policy narratives while preserving the flexibility needed for operational forecasting (Berg & Portillo, 2018). In this sense, semi-structural models occupy an intermediate position in the history of macroeconometric modeling: more theoretically disciplined than traditional reduced-form forecasting models, but more empirically adaptable and institutionally usable than fully structural DSGE frameworks.

This flexibility proved particularly valuable in practice. As central banks accumulated experience with inflation targeting, it became increasingly clear that structural change, financial crises, commodity-price shocks, institutional reforms, and shifts in policy regimes frequently altered economic relationships in ways that were difficult to capture within tightly specified structural models (Mishkin, 2007; O. Blanchard, 2018). Semi-structural frameworks provided policymakers with greater freedom to adapt model specifications, revise assumptions, and incorporate new information while preserving a coherent economic narrative. The Global Financial Crisis further reinforced their attractiveness. While the crisis exposed important weaknesses in many DSGE frameworks, it also highlighted the need for forecasting systems capable of rapidly incorporating judgment, financial-sector developments, and alternative policy scenarios. Semi-structural models proved particularly well suited to this environment because they could integrate model-based analysis with expert assessment in a transparent and operationally manageable way.

The simplicity of this structure was one of the principal reasons for its success. Policymakers could understand the mechanisms driving the forecast, communicate them to decision-makers, and modify assumptions when economic conditions changed. Unlike larger structural models, semi-structural frameworks remained sufficiently transparent that analysts could readily trace the sources of forecast revisions and policy recommendations (Black et al., 1994; Coletti et al., 1996; Berg et al., 2006; Berg & Portillo, 2018). This transparency became particularly valuable in inflation-targeting regimes, where effective policy communication increasingly required central banks to explain not only their decisions but also the economic reasoning underlying their forecasts (Svensson, 1997; Mishkin, 2007).

A further innovation that contributed to the operational success of semi-structural models was their treatment of economically meaningful but unobservable concepts. Monetary policymakers routinely rely on variables such as potential output, the output gap, neutral interest rates, equilibrium exchange rates, trend productivity growth, and underlying inflationary pressures, even though these concepts must be inferred from observable macroeconomic data rather than measured directly (Laubach & Williams, 2003; Orphanides, 2002; Hamilton, 1994). Earlier policy analysis often relied on judgmental assessments, univariate filters, or separate auxiliary estimates of these variables. Semi-structural FPAS frameworks made it possible to embed such latent concepts directly within the forecasting model and to estimate them in a way that was consistent with the model's economic relationships (Berg et al., 2006; Berg & Portillo, 2018).

State-space methods and Kalman filtering were central to this process, although they are not specific to semi-structural models. Their importance in this context was that relatively parsimonious QPM-type frameworks made filtering transparent, interpretable, and operationally manageable in regular forecast rounds (Harvey, 1989; Hamilton, 1994; Durbin & Koopman, 2012). The Kalman filter operates recursively, starting from an initial estimate of the latent state and its uncertainty, which may be specified using prior information, unconditional moments of the model, or iterative estimation procedures. As new observations become available, the filter updates its assessment of unobserved variables by balancing the information contained in the data against the restrictions imposed by the model. A subsequent smoothing step uses information from the full sample to refine historical estimates, making the distinction between real-time filtered estimates and ex-post smoothed estimates particularly important for policy analysis (Hamilton, 1994; Harvey, 1989; Durbin & Koopman, 2012).

Within FPAS frameworks, these filtered and smoothed estimates became much more than technical inputs to estimation. They provided model-consistent assessments of cyclical positions, equilibrium gaps, underlying inflationary pressures, policy stances, and structural shocks. This made it possible to begin each forecast round from an internally consistent interpretation of the economy's initial conditions: whether demand was above or below potential, whether inflationary pressures were broadening or fading, whether monetary policy was restrictive or accommodative, and whether external shocks were driving domestic outcomes. Filtering therefore helped connect the historical interpretation of recent developments with the projected path of the economy. It also supported model diagnostics, historical shock decompositions, and the construction of coherent policy narratives (Orphanides, 2002; Laubach & Williams, 2003; Berg et al., 2006; Berg & Portillo, 2018).

This link between model structure, filtering, and forecast construction became one of the defining features of semi-structural FPAS systems. Forecasts were no longer interpreted as mechanical projections generated by a model in isolation. Instead, model outputs provided a disciplined starting point for a broader process of policy interpretation, scenario analysis, risk assessment, and communication. Historical shock decompositions played an important role in this process by attributing observed developments to demand, supply, financial, external, or policy disturbances. Institutions such as the Czech National Bank have routinely used decomposition charts to explain changes in inflation, output, and monetary conditions within a coherent economic framework (Andrle et al., 2009; Benes et al., 2010). Such exercises help policymakers move beyond the description of observed outcomes and construct economically meaningful interpretations of past developments.

Judgment remains essential in this process, but semi-structural FPAS frameworks changed the way judgment enters the forecast. In earlier macroeconometric systems, forecasts often relied on extensive discretionary adjustments, while the first generation of inflation-targeting models sought to impose greater analytical discipline on the forecasting process. Modern FPAS frameworks attempted to reconcile these approaches by embedding judgment within a transparent and structured modeling environment (Berg et al., 2006; Berg & Portillo, 2018). Expert assessment is particularly important when forecasters must interpret incoming information that is not yet fully reflected in official data releases, including business surveys, market intelligence, policy announcements, temporary disruptions, changes in financial conditions, or high-frequency indicators. In such cases, judgment helps translate qualitative and partial information into quantitative adjustments that can be evaluated within the model-based forecast.

Judgment also enters the forecast through the specification of conditioning assumptions, scenario design, and the interpretation of unusual events. Baseline projections typically require assumptions regarding foreign demand, commodity prices, exchange rates, fiscal policy, financial conditions, and global economic developments. These assumptions may be informed by market expectations, external forecasts, satellite models, or institutional surveillance, but their final specification often reflects policy expertise and institutional assessment (Berg et al., 2006; Berg & Portillo, 2018). The same logic applies to scenario analysis and risk assessment, where policymakers evaluate how the economy might evolve under alternative assumptions regarding commodity prices, exchange rates, fiscal policy, global growth, financial conditions, or monetary policy responses. Such exercises have become standard features of publications such as the Bank of England’s Monetary Policy Report, the ECB’s staff projections, and IMF surveillance exercises. Judgment becomes especially important when assessing events that lie outside the historical experience represented in the model, including financial crises, geopolitical disruptions, pandemics, or major policy-regime changes. In such cases, expert assessment does not replace model-based analysis, but helps translate qualitative information and unusual developments into explicit, transparent, and internally consistent scenarios. Forecasting within an FPAS framework is therefore best understood as an iterative process that combines model-based projections, incoming data, institutional knowledge, and policy judgment rather than as the mechanical output of a single model (Goodhart, 2001; Mishkin, 2007; Berg et al., 2006; Berg & Portillo, 2018).

This broader view of forecasting also changed the way semi-structural models were validated. During the 2000s, and especially after the Global Financial Crisis and subsequent episodes of structural change, policy institutions increasingly needed to understand not only whether forecasts were accurate, but also why forecasts succeeded or failed (Caballero, 2010; O. Blanchard, 2018). Many FPAS implementations therefore complement conventional forecast evaluation with diagnostic exercises such as historical decompositions, forecast revisions, real-time versus ex-post comparisons, out-of-sample forecasting performance, and assessments of whether estimated shocks correspond to known economic events (Berg et al., 2006; Berg & Portillo, 2018; Pranovich et al., 2021). This reflects the fact that semi-structural models are evaluated not only as forecasting devices, but also as tools for economic interpretation. A forecast may be statistically accurate for the wrong reasons, while a structurally coherent explanation may provide valuable policy insights even when forecasting performance temporarily deteriorates. The credibility of semi-structural models therefore rests on a dual requirement: they must generate useful forecasts, but they must also produce economically plausible narratives about macroeconomic developments, policy decisions, and the shocks driving the forecast.

The role of semi-structural models within policy institutions has therefore evolved considerably since the first generation of QPMs developed during the 1990s. Early implementations focused primarily on generating baseline forecasts and supporting monetary-policy decisions (Black et al., 1994; Coletti et al., 1996). Over time, however, these models became embedded within broader Forecasting and Policy Analysis Systems, where they support not only forecasting, but also scenario analysis, risk assessment, policy deliberation, communication, and the interpretation of economic developments (Berg et al., 2006; Berg & Portillo, 2018). This evolution reflects more than a particular modeling innovation. It illustrates a broader process of institutional learning in which policymakers gradually recognized that effective forecasting systems require more than statistical accuracy or theoretical consistency alone. Modern FPAS frameworks combine data, economic theory, institutional knowledge, and expert judgment within a coherent decision-making process. While forecasts are generated within a structured model environment, the process itself is not fully automated. Models cannot capture every source of information relevant for policy decisions, particularly during periods of structural change, elevated uncertainty, or rapidly evolving economic conditions. As a result, expert assessment remains an integral component of the forecast round, complementing model-based analysis with institutional knowledge, high-frequency indicators, and real-time developments that may not yet be reflected in official data.

The expanded role of semi-structural models also raised new questions regarding model credibility, forecast evaluation, and institutional accountability. Unlike purely statistical forecasting systems, semi-structural models are expected not only to predict economic developments, but also to provide economically meaningful interpretations of observed outcomes and policy decisions (Berg et al., 2006; Berg & Portillo, 2018). Forecast accuracy therefore remains important, but it is not sufficient on its own. Policymakers are also concerned with the plausibility of transmission mechanisms, the stability of estimated gaps and equilibrium concepts, the consistency of historical shock decompositions, and the usefulness of the resulting narrative for policy communication. In this respect, semi-structural models occupy a distinctive position within modern policy institutions: they provide enough structure to organize economic thinking and policy analysis, while remaining flexible enough to incorporate judgment, real-time information, and changing institutional requirements.

The combination of economic structure, empirical flexibility, and transparent policy interpretation proved attractive to a growing number of institutions. Over time, semi-structural frameworks spread far beyond the small group of inflation-targeting central banks that initially pioneered their use. This international diffusion occurred in several waves. The first generation emerged in early inflation-targeting central banks such as the Bank of Canada and the Reserve Bank of New Zealand during the 1990s (Black et al., 1994; Coletti et al., 1996; Drew et al., 2002). The Bank of Canada's Quarterly Projection Model became one of the earliest operational forecasting frameworks explicitly designed for inflation targeting, while the Reserve Bank of New Zealand developed an integrated FPAS architecture that combined structured forecast rounds, semi-structural models, and judgmental adjustments (Bank of Canada, 2015; Reserve Bank of New Zealand, 2018).

A second wave followed during the 2000s, as inflation targeting spread across emerging-market economies and central banks sought forecasting systems capable of supporting increasingly sophisticated policy frameworks (Berg et al., 2006).

The Czech National Bank became one of the most influential examples of FPAS implementation, with successive generations of models, including QPM, g2, g3, and g3+, playing a central role in monetary policy analysis and inflation reports (Andrle et al., 2009; Brazdik et al., 2020). Similar semi-structural or suite-based approaches were adopted, adapted, or developed by institutions such as Norges Bank, Sveriges Riksbank, the Reserve Bank of Australia, Banco Central de Chile, Banco de la República in Colombia, the South African Reserve Bank, the National Bank of Ukraine, the National Bank of Georgia, the Central Bank of Armenia, the Central Bank of Hungary, and Bangko Sentral ng Pilipinas. Although these frameworks differed in complexity and institutional context, they shared a common philosophy: combine economic structure, empirical realism, and policy judgment within a transparent operational framework.

A third phase emerged after the Global Financial Crisis, when FPAS methodologies became a standard component of IMF technical assistance and were adopted by a growing number of central banks across Eastern Europe, Latin America, Africa, and Asia (Berg & Portillo, 2018). The IMF played a major role in disseminating semi-structural modeling practices through technical assistance, training, and model development. Its semi-structural frameworks included the Global Projection Model (GPM), GPM6, the Forecasting and Policy Analysis System (FPAS), the Flexible System of Global Models (FSGM), and the Practical Model (PAM) family used extensively in emerging-market and developing economies (Berg et al., 2006; Berg & Portillo, 2018; Carabenciov et al., 2008; Andrle et al., 2015b,a). In parallel, larger policy institutions developed suite-based forecasting systems in which semi-structural models interacted with DSGE and statistical models. The Bank of England's framework evolved from large-scale macroeconometric systems toward model suites centered on frameworks such as COMPASS, while the ECB and the Eurosystem increasingly relied on broad model suites combining semi-structural forecasting tools, DSGE models, and statistical systems such as ECB-BASE and related multicountry frameworks (Burgess et al., 2013; K. Christoffel et al., 2008).

The institutional diffusion of semi-structural models illustrates why they became so influential in modern policy practice. Their success did not rest on a single technical innovation, but on their ability to provide an operational language for inflation targeting, forecast rounds, scenario analysis, policy communication, and structured judgment. Rather than emerging from a major theoretical breakthrough, QPM-type frameworks evolved from the accumulated practical experience of central banks and international institutions working with both statistical forecasting tools and DSGE models. Their lasting contribution lies in the modeling philosophy they helped institutionalize: combining enough economic structure to discipline policy interpretation with enough empirical flexibility to remain useful in real-time forecasting environments. By selectively incorporating key transmission mechanisms from DSGE models while retaining the adaptability needed for forecast production, scenario analysis, and policy communication, semi-structural frameworks became a practical bridge between economic theory and the operational requirements of policy institutions (Berg et al., 2006; Berg & Portillo, 2018).

Their widespread adoption also reflects a broader shift away from the search for a single best model and toward integrated forecasting systems that combine complementary analytical tools. Semi-structural models proved especially well suited to this environment because they matched the institutional realities of policy work: forecasts must be produced repeatedly, revised transparently, explained coherently, and used to support decisions under uncertainty. In contrast to model classes whose appeal rested primarily on theoretical purity or statistical performance, semi-structural models offered a framework in which data, economic structure, expert judgment, and policy communication could be organized within a single forecast process. This is why they came to occupy a central position in many modern FPAS architectures. They provide the operational core around which short-term empirical tools, structural models, scenario analysis, and policy deliberation can be integrated into a coherent system for forecasting and policy analysis.

23.6 Conclusion: From Models to Policy Frameworks

The evolution of macroeconomic forecasting and policy advising over the past seventy years is often described as a sequence of competing modeling paradigms. Large-scale macroeconometric systems were followed by time-series methods, DSGE models, and semi-structural frameworks, each addressing perceived weaknesses in earlier approaches. Viewed from today's perspective, however, this history appears less as a succession of methodological replacements than as a process of institutional learning. Policy institutions did not converge toward a single dominant framework. Instead, they gradually developed a diverse set of analytical tools suited to different forecasting, diagnostic, and policy-analysis tasks.

This evolution also transformed the role of macroeconomic models within policy institutions. Early forecasting systems were primarily designed to generate projections of key macroeconomic variables. Modern forecasting frameworks pursue a broader objective. Policymakers require tools capable not only of predicting economic developments, but also of interpreting shocks, evaluating alternative policy responses, communicating risks, and organizing coherent narratives about the economy. Forecasting has therefore become inseparable from policy analysis.

The historical experience reviewed in this chapter suggests that different modeling traditions made distinct contributions to this broader policy process. Statistical and econometric models remain indispensable for nowcasting, short-term forecasting, and signal extraction. DSGE models contribute theoretical discipline, counterfactual analysis, and welfare-based policy evaluation. Semi-structural models provide the operational environment in which forecasts, scenarios, judgment, and policy discussions are organized. Modern FPAS architectures emerged from the recognition that these functions are complementary and that no single model can perform all of them equally well.

A second major lesson concerns the growing importance of international linkages. From the earliest multicountry forecasting exercises to contemporary frameworks such as GIMF, FSGM, and multicountry FPAS systems, policymakers have repeatedly sought tools capable of tracing how shocks propagate across borders. Globalization, financial integration, commodity-price fluctuations, and international policy spillovers have transformed forecasting from a predominantly national exercise into one that increasingly requires a global perspective. Modern policy analysis therefore depends not only on understanding domestic transmission mechanisms, but also on assessing how foreign developments, global financial conditions, and policy actions abroad interact with domestic outcomes.

Looking forward, future developments are likely to deepen this integration rather than overturn it. Machine learning, high-frequency data, real-time indicators, and advances in heterogeneous-agent macroeconomics are expanding the analytical frontier. Yet these innovations are unlikely to eliminate the need for model diversity. They are more likely to become additional components of forecasting systems that combine multiple sources of information, different modeling traditions, and institutional expertise within a disciplined policy process.

The central lesson of modern forecasting practice is therefore not the superiority of any individual model class, but the importance of organizing diverse analytical tools within a coherent institutional framework. Effective policy analysis combines empirical evidence, economic theory, institutional knowledge, and expert judgment in a transparent and disciplined manner. The value of models lies not in replacing policy judgment, but in improving the conditions under which such judgment is exercised. Well-designed models provide a structured starting point for policy discussions, clarify assumptions, reveal trade-offs, discipline narratives, and help rule out internally inconsistent or poorly specified policy options. At the same time, the need for counterfactual analysis ensures that policy institutions cannot rely on purely empirical forecasting tools alone. The enduring contribution of FPAS frameworks is that they provide an environment in which models are not isolated technical devices, but components of an integrated process for understanding economic developments, evaluating policy alternatives, and supporting decisions under uncertainty.

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