Essays on Forecasting Methods and Monetary Policy Evaluation

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To my family, for their support and encouragement. To those who are gone. To those who are coming.

“... in one’s own environment, one takes too much for granted, without asking why things are the way they are.” – Joseph Stiglitz
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The collapse of the financial system in the US during the summer of 2008 spread to the global economy and it produced an increase in macroeconomic volatility together with a significant drop in production and employment levels. Public institutions implemented exceptional fiscal and monetary policies to face the effects of the crisis. As a consequence, the balances of the central banks increased considerably and new concerns emerged about the financial stability of some governments after their extraordinary fiscal efforts. This exceptional economic context with no precedents in the recent history has led to a vast and proliferating literature on the identification of the transmission mechanisms of these events and the implementation and assessment of the most appropriate public policies.

Moreover, the most recent developments in information technology gives access to a massive amount of data and opens new horizons for economic research. However, the processing of large sets of information, the selection of the most appropriate indicators among those which are available, and the elaboration of methods to handle these data also entail new challenges for researchers. The three chapters of this thesis deal with the development and application of techniques that contribute to solving these concerns and focus on their implementation to address some of the important issues arising in the economic literature after the crisis of 2008 as predicting the economic evolution, identifying changing macroeconomic patterns and assessing the effects of monetary policy in this new context.

The first chapter compares the properties of two dimension reduction techniques for the incorporation of larger amount of information into economic models. These methods assume that the behavior of the economy may be explained by a small number of factors which are not directly observable as, for instance, the business cycle, factors representing real and nominal variables, monetary and financial conditions, etc. Under this assumption, Dynamic
Factor Models estimate a number of latent factors that explain most of the co-movement of macroeconomic indicators. This feature allows the inclusion of greater amount of information in economic models preserving a parsimonious specification. However, Dynamic Factor Models can be estimated under two assumptions: considering that the information needed to capture the behavior of the economy is included in a small set of key macroeconomic indicators or, on the contrary, that all available information can be used since there is no reason to exclude any of them. Depending on the decision taken by the researcher at this point, we can use two versions of the Dynamic Factor Models: i) a version where factors are estimated from a reduced number of observable indicators, Small Scale Dynamic Factor Models, or ii) by estimating the factors from a large dataset, Large Scale Dynamic Factor Models. Moreover, the decision about the amount of information included in each of these models for the estimation of the latent factors has consequences for the statistical properties of the estimation process.

For this reason, the first chapter contributes to the literature which has separately treated Small Scale Dynamic Factor Models (Stock and Watson, 1991) and Large Scale Dynamic Factor Models (Doz, Giannone and Reichlin, 2006) through an empirical comparison of both. The models are evaluated by comparing the forecast power of the factors estimated under both methodologies for Gross Domestic Product in order to assess which of the two versions is able to capture more precisely the overall evolution of the economy. This comparison is carried out for six different countries presenting differences in the availability of data and allowing us the identification of the most accurate model for each country.

Going further, Dynamic Factor Models assume a linear relationship between observable variables and latent factors. This implies that the interaction between the macroeconomic data and the forces driving its behavior remains invariant along the sample period. Such an assumption was more suitable before the financial crisis of 2008, a period which was characterized by low macroeconomic volatility and long periods of expansion in most developed economies. However, after 2008 there was an abrupt and unprecedented change in the evo-
olution of the main macroeconomic indicators. In the particular case of the US, the Federal Reserve fought this extraordinary and adverse scenario by reducing the official interest rates to their zero lower bound and increasing liquidity by the massive acquisition of assets bought with money newly created.

This scenario with low inflation, high unemployment, drops in production, interest rates close to zero and monetary aggregates at their highest level suggests a change in the economic situation and patterns in the interaction between monetary policy and the real economy where the linear assumption of the Dynamic Factor Models may become unrealistic. For this reason, the second chapter of this thesis proposes a modification of the Large Scale Dynamic Factor Models where the parameters describing the macroeconomic relationships are permitted to change depending on the identification of different structural scenarios. This alternative specification allows us the estimation of different reactions to monetary policy decisions in each scenario. It is carried out using a large data set of 110 monthly variables from the US and by allowing the dynamics of the underlying factors to evolve following a Markov Switching process. This specification identifies the presence of different structural scenarios based on the behavior of a large set of indicators and provides estimates of the changes in the monetary policy transmission mechanisms within a sample period corresponding with the last 40 years.

The classification of the different structural periods provided by this methodology shows that the crack of 2008 was followed by a period of high volatility and recession. However, it had no permanent effects on the structural situation of the US and after a few years the macroeconomic patterns and interactions went back to the state prior to that of the summer of 2008. However, the current monetary conditions are still unusual due to the zero lower bound of the official interest rates and the high level of monetary aggregates. This exceptional situation in a context where the real economy seems to be recovering requires the identification of an optimal exit strategy towards traditional monetary policy measures. The third chapter of this thesis focuses on this issue.
The return to a normal situation should be designed taking into account that an early withdrawal of stimulus programs could reduce the economic activity and employment more than desired while excessive prolongation of these stimuli may generate excessive dependence on the liquidity injections and, ultimately, could lead to strong inflationary pressures. In addition, the current extraordinary monetary context, with no precedents in the recent history, adds uncertainty about the consequences of the withdrawal of the stimuli. The third chapter of this thesis tackles this issue by suggesting a methodology based on the use of Small Scale Dynamic Factor Models for the assessment of the consequences for the main macroeconomic indicators of the decisions taken by the monetary authorities.

It is important to notice that these models are able to include in the estimation process an information set with indicators available for different dates because of their differences in the publication lag. Thus, for the evaluation of the monetary policy decisions, it is proposed to enlarge the set of information publicly available at a given date with the future evolution of the monetary policy rate which is only known by the policymaker, for example, the path to be followed by interest rates over the next year to reach levels similar to those that prevailed during the pre-financial crisis period. Predictions using this data set are based on both the recent evolution of the indicators included in the model as well as the evolution of the monetary variables set by the policymaker for the future. Therefore, the assessment of the consequences of this monetary policy path can be carried out by comparing these predictions with others using an alternative path as, for example, by keeping interest rates unchanged for the coming year. This comparison allows us to evaluate the consequences of each of these possible monetary policy paths in the future evolution of the indicators included in the model. In particular, predictions for GDP, employment, sales, industrial production, income and price are carried out for five possible paths which could be followed by the Federal Reserve. The evaluation of the outcomes shows the extent to which an expansionary monetary policy would stimulate real economic performance while a contractionary policy reduces the rates of growth of the activity and employment indicators. In addition, the
evolution of prices remains very similar under contractionary and expansionary paths, a result which is consistent with the low inflation rate observed after the implementation of the extraordinary monetary stimuli implemented after the financial crisis and the recession.

To conclude, throughout the three chapters of this thesis, Dynamic Factor Models are shown as a powerful tool for the analysis of monetary policy as well as for the assessment and prediction of the economic performance even under restrictions in the data availability such as those that take place in developing countries. The results of the thesis show how the financial crisis of 2008 led to changes in macroeconomic and monetary interactions in a structural scenario different from those in the previous years, characterized by low volatility and long expansions. Finally, it proposes the implementation of these models for the identification of the optimal exit strategy towards a traditional monetary situation similar to the pre-Great Recession period.
Introducción (extendida en Español)

El colapso del sistema financiero en EEUU durante el verano de 2008 se transmitió a la economía global y tuvo importantes consecuencias como el aumento de la volatilidad macroeconómica o severas caídas de los niveles de producción y empleo. También se observó heterogeneidad en la concreción de medidas públicas para contrarrestar la crisis, un incremento del balance de las instituciones monetarias tras la implementación de estímulos de una magnitud excepcional y dudas sobre la estabilidad financiera de algunos gobiernos tras la realización de importantes esfuerzos fiscales. Este contexto económico excepcional y sin precedentes ha dado lugar a una basta y prolífera literatura acerca de la identificación de los mecanismos de transmisión de estos sucesos así como de la elaboración o evaluación de las políticas públicas más adecuadas.

Por otra parte, el importante desarrollo de las tecnologías de la información y la comunicación que ha tenido lugar en los últimos años da acceso a gran cantidad de datos y abre nuevos horizontes para la investigación económica. Sin embargo, el tratamiento de grandes conjuntos de información, la selección de los indicadores más adecuados dentro de todos los disponibles para un determinado propósito y el desarrollo de técnicas que permitan manejar esos datos supone también nuevos desafíos para el investigador. Los tres capítulos que componen esta tesis tratan sobre el desarrollo e implementación de técnicas que contribuyen a solución de estos aspectos y se centran en su aplicación para abordar algunas de las importantes cuestiones que surgen en la literatura económica tras la crisis 2008 como la predicción la evolución económica, identificación cambios en los patrones y relaciones macroeconómicas y la valoración los efectos de la política monetaria en este nuevo contexto.

El primero de los capítulos compara las propiedades de dos métodos de reducción de
dimensión de la información para su incorporación en modelos económicos. Estos métodos asumen que el comportamiento conjunto de la economía está explicado por un número reducido de factores que no son directamente observables como, por ejemplo, el ciclo económico, factores representativos de variables reales y nominales, de la situación monetaria y financiera, etc. Bajo esta idea, los Modelos de Factores Dinámicos estiman una serie de factores latentes capaces de explicar la mayor parte del co-movimiento de los indicadores macroeconómicos. Esta característica permite la inclusión de una mayor cantidad de información en los modelos económicos preservando una especificación parsimoniosa y, por tanto, viable a través de las técnicas de estimación convencionales generalmente implementadas con pequeños conjuntos de datos. Ahora bien, los Modelos de Factores Dinámicos pueden estimarse bajo dos presunciones: considerando que la información necesaria para capturar el comportamiento conjunto de la economía, y la consecuente estimación de factores, está incluida en un pequeño grupo de indicadores macroeconómicos clave que puede ser seleccionados bajo la experiencia del investigador o de acuerdo con ciertos criterios técnicos y estadísticos o, por el contrario, que toda la información posible debe usarse para estimar estos factores ya que no hay motivo para excluir ninguna de la que esté disponible. Dependiendo de la decisión tomada por el investigador en este punto, podemos utilizar dos versiones de los Modelos de Factores Dinámicos: la versión en la que los factores son estimados a partir de un número reducido de indicadores observables, Modelos de Factores Dinámicos de Pequeña Escala, o utilizar factores estimados basados en un conjunto de datos más grande, Modelos de Factores Dinámicos de Gran Escala. Más allá de las decisiones relativas al volumen de información incluido en cada uno de estos modelos para la estimación de estos factores latentes, la implementación de cada versión entraña consecuencias con respecto a las propiedades teóricas y estadísticas del proceso de estimación y los factores que dan como resultado.

Por ese motivo, este primer capítulo contribuye a la literatura que anteriormente ha tratado por separado los Modelos de Factores Dinámicos de Pequeña Escala (Stock y Watson, 1991) y los Modelos de Factores Dinámicos de Gran Escala (Doz, Giannone y Reichlin, 2006)
a través de la comparación de ambos desde un punto de vista completamente empírico. A fin de valorar cuál de las dos versiones es capaz de capturar con mayor precisión la evolución y comportamiento de la economía, los dos modelos son evaluados a través de la comparación del poder predictivo de ambas metodologías para la evolución futura del Producto Interior Bruto. Debe tenerse en cuenta que las características estadísticas de los datos observables que dan lugar a los factores juegan un papel importante en la precisión de las estimaciones. Por este motivo, el ejercicio comparativo de los dos modelos es reproducido en seis países distintos a fin de valorar la medida en que los datos disponibles para cada uno de estos países se ajustan mejor a los requisitos teóricos de los modelos de pequeña o de gran escala. Para este fin, se utilizan datos de países en desarrollo ya que este tipo de países suele presentar una menor disponibilidad de datos, con series que pueden presentar una menor longitud temporal y en ocasiones con valores perdidos a mitad de muestra. En concreto, en este capítulo se seleccionaron seis países latinoamericanos en los que ambas versiones de los Modelos de Factores Dinámicos habían sido implementados previamente pero por separado, Camacho y Perez Quiros (2011), en el caso del modelo de pequeña escala y Liu, Matheson y Romeu (2012), en el de gran escala.

A través de la comparación del error de predicción fuera de muestra de cada uno de los modelos en estos seis países se identifica cuál es el modelo más apropiado en cada uno de ellos para la realización de predicciones en dos horizontes temporales distintos: el correspondiente con el dato del Producto Interior Bruto que será publicado en el trimestre en que se realiza la predicción y, en segundo lugar, el correspondiente con el dato que se publicará en el siguiente trimestre. Los resultados muestran como el Modelo de Factores Dinámicos de Pequeña Escala produce predicciones más precisas en unos países mientras que en otros es preferible la utilización del Modelo de Factores Dinámicos de Gran Escala. También se dan casos en los que cada uno de los modelos es más preciso que su rival dependiendo del horizonte temporal en el que se realice la predicción dentro de un mismo país. Esto sugiere que ninguna de las limitaciones teóricas acerca de las características de los datos observables
y el proceso de estimación de cada metodología es suficientemente determinante como para descartar un modelo en favor de otro una vez implementados con datos reales.

Por otra parte, tanto en el modelo de pequeña escala como el de gran escala se asume que la relación entre los factores latentes y las variables observables es lineal. Esto implica que la interacción entre los datos macroeconómicos y los factores que explican su comportamiento se asume invariante a lo largo del periodo de tiempo que comprende la muestra de datos utilizada. Esta característica resultaba más apropiada en el pasado, especialmente durante los años comprendidos entre mediados de los ochenta y las fechas anteriores a la Gran Recesión que siguió a la crisis financiera de 2008. Este periodo estuvo caracterizado por una escasa volatilidad macroeconómica y largos periodos de expansión en la mayoría de las economías desarrolladas. Sin embargo, tras la recesión que tuvo lugar en 2008 hubo un cambio abrupto y sin precedentes en la evolución de los principales indicadores macroeconómicos como producción, empleo y precios. En el caso particular de EE.UU. la Reserva Federal combatió este extraordinario y adverso escenario económico con una serie de medidas excepcionales orientadas, en primer término, a contrarrestar la escasez de liquidez del sistema financiero y, en segundo lugar, a combatir el desempleo y recuperar los niveles de producción previos a la crisis financiera. Estas medidas poco convencionales se materializaron en la reducción de los tipos de interés oficiales hasta a su mínimo posible cercano a cero y la inyección masiva de dinero en el sistema a través de la compra masiva de activos inmobiliarios y deuda pública con dinero de nueva creación por parte de la Reserva Federal.

Esta situación, con tasas de variación en los precios muy reducidas o incluso deflación, niveles de desempleo muy elevados, fuerte caída de la producción, tipos de interés próximos a cero y agregados monetario en niveles muy superiores a los previamente observados como consecuencia de la compra masiva de activos sugieren la presencia de un escenario estructural distinto al observado durante los treinta años previos a la crisis financiera de 2008 que ponen en tela de juicio la idoneidad de los modelos de factores dinámicos para la caracterización del comportamiento macroeconómico debido, precisamente, a la presunción de esa relación
La literatura previa ha mostrado como los Modelos de Factores Dinámicos de Gran Escala son una herramienta útil para la estimación de los efectos de las decisiones en materia de política monetaria en la economía. El buen comportamiento del modelo para la estimación de estos mecanismos de transmisión de política monetaria ha sido demostrado mediante la comparación de sus resultados con otras metodologías en las que no se utilizan técnicas de reducción de dimensión de la información y que, consecuentemente, incluyen un conjunto de información más reducido como en el caso de los modelos de Vectores Auto Regresivos. Estos modelos se basan en la estimación de las correlaciones dinámicas de un pequeño conjunto de indicadores macroeconómicos, donde se incluye alguna variable representativa de la política monetaria, como los tipos de interés, y permiten evaluar los efectos de un cambio en la dinámica de dicha variable en las otras incluidas en el modelo a lo largo del tiempo (Funciones de Respuesta al Impulso). Bajo esta metodología, ampliamente utilizada en la literatura tanto para predicción como para análisis estructural, los efectos de las decisiones en materia monetaria han dado lugar a ciertos resultados empíricos en conflicto con la teoría económica. Un ejemplo es la estimación de subidas en el nivel de precios como consecuencia de incrementos de los tipos de interés oficiales o de una política monetaria contractiva, conocido como el Price Puzzle (Sims, 1992). También han dado lugar a predicciones en la reacción de los tipos de cambio que tiene lugar con un considerable retraso con respecto al momento en el que se simula la variación en los tipos de interés en lugar de una reacción instantánea tal y como predice la teoría económica, fenómeno este conocido como Delayed Overshooting Puzzle (Eichenbaum and Evans, 1995). Una posible explicación para estos resultados es precisamente la pequeña cantidad de información que puede ser incluida en los modelos de Vectores Auto Regresivos. Esta limitación se debe a que el número de indicadores debe ser pequeño para la correcta estimación de los parámetros que describen la relación dinámica entre ellos. Así, usando estos modelos, es probable que se dé una situación en la que algún
indicador macroeconómico que contenga información relevante para la identificación de los mecanismos de trasmisión de la política monetaria quede excluido del proceso de estimación y, en este caso, que los resultados obtenidos estén sesgados debido precisamente a la omisión de esta información relevante, hecho este que podría explicar la presencia de los Puzzles anteriormente citados. Sin embargo, el desarrollo e implementación de Modelos de Factores Dinámicos de Gran Escala para la evaluación de los efectos de política monetaria es capaz de conciliar los resultados empíricos con la teoría económica resolviendo tanto el Price Puzzle como el Delayed Overshooting Puzzle (Gambetti and Forni, 2010) a través de la inclusión de una mayor cantidad de información resumida mediante la implementación de las técnicas de reducción de dimensión en que se basan estos modelos de gran escala. Además, y contrariamente a los modelos de Vectores Auto Regresivos donde los efectos de un cambio en la política monetaria solo puede ser evaluados en el reducido conjunto de indicadores incluido en el modelo, los Modelos de Factores Dinámicos de Gran Escala permiten valurar estos mecanismos de transmisión en un amplio conjunto de indicadores pertenecientes a cualquiera de las categorías macroeconómicas en las que el investigador o el ente responsable de la política monetaria pueda estar interesado.

Sin embargo, como ya se ha señalado anteriormente, las graves consecuencias de la Gran recesión en el contexto económico con fuertes caídas de la producción empleo y precios junto con la nueva situación tipos de interés en mínimos y agregados monetarios en máximos históricos sugieren la presencia de un cambio en los patrones que describen la interacción y relaciones entre los distintos elementos de la macroeconomía y la política monetaria. Por este motivo el segundo capítulo de la tesis propone una modificación de los Modelos de Factores Dinámicos de Gran Escala en la que deja de asumirse un relación invariante entre las fuerzas que explican el comportamiento económico, los factores, y las variables observables y que, por tanto, nos permita así identificar cuáles son las repercusiones y efectos de la política monetaria en la economía en su conjunto en distintos escenarios macroeconómicos a lo largo del tiempo.
Inicialmente, a fin de valorar si esta modificación en los Modelos de Factores Dinámicos es necesaria y apropiada y, al mismo tiempo, de si los mecanismos de transmisión de política monetaria han sido afectados durante el periodo posterior a la crisis financiera tal y como podrá intuirse a través de la simple observación de algunos agregados macroeconómicos claves, se estiman los resultados proporcionados por un Modelo de Factores Dinámicos convencional en el que la posible presencia de cambios en los parámetros del modelo no es permitida para una muestra de datos que se va ampliando progresivamente. Este ejercicio se centra en el caso particular de EE.UU. En concreto, se seleccionaron 110 variables macroeconómicas en frecuencia mensual consideradas como representativas de la economía estadunidense en su conjunto para el periodo comprendido entre abril de 1974 hasta noviembre de 2013. Mediante el cálculo de las Funciones de Respuesta al Impulso, se realizó una primera estimación de cuáles serían las consecuencias de una subida de los tipos de interés oficiales de 50 puntos básico para estas 110 variables utilizando únicamente información entre abril de 1974 hasta enero de 2005. En un segundo paso, las Funciones de Respuesta al Impulso para un cambio de igual magnitud en los tipos oficiales es estimado usando ahora un mes más de información, desde abril de 1974 hasta febrero de 2005. Este proceso en el que la muestra se va aumentando con una observación mensual más en el conjunto de datos es repetido iterativamente hasta que la última observación de la que se dispone, correspondiente con noviembre de 2013, es incluida. En la comparación gráfica de la evolución de las Funciones de Respuesta al Impulso estimadas en cada uno de los pasos de este proceso iterativo se observa como la reacción de las 110 variables a una subida en los tipos de interés es muy similar durante los primeros pasos. Sin embargo, en las estimaciones en las que se incluyen observaciones correspondientes a las fechas de la crisis financiera del verano de 2008 se observa un aumento de la magnitud de las respuestas estimadas que se mantiene hasta finales de 2013. Este resultado muestra como la economía se vuelve más reactiva a las decisiones en materia de política monetaria tras la recesión de 2008 y además implica importante cuestiones que deben ser consideradas por el investigador. Esto se debe al hecho de que estos hallazgos generan incertidumbre acerca de cuáles deben ser las fechas y dimensión temporal de la muestra de datos.
más adecuada para la correcta estimación de las Funciones de Respuesta al Impulso de los distintos indicadores macroeconómicos a la política monetaria en las condiciones económicas actuales. Una posible respuesta a esta cuestión sería que toda la muestra disponible debe ser incluida en el modelo a fin de obtener estimaciones más precisas debido al aumento del ratio entre el número de observaciones y la cantidad de parámetros a estimar. Pero esta decisión suscitaría dudas acerca de si los resultados obtenidos bajo este criterio están distorsionados por la inercia de los datos posteriores a la crisis financiera de 2008, caracterizados por un periodo de más volatilidad que ya ha quedado atrás. Por este motivo, es necesario un proceso de estimación que permita resolver estas dudas e identificar el periodo muestral más adecuado para la representación de las características económicas estructurales y mecanismos de transmisión de la política monetaria que se dan en la actualidad.

Este aspecto y sus consecuencias en la estimación de los factores latentes, conocido como presencia de inestabilidad estructural, ha sido previamente explorado en la literatura de los Modelos de Factores Dinámicos de Gran Escala mediante la simulación de los datos con métodos Monte Carlo que son posteriormente utilizados para la estimación de los parámetros del modelo (Banerjee, Marcellino y Masten, 2008). Otros artículos se han centrado también en esta problemática a través de la suposición de que realmente existe un ruptura estructural en el periodo analizado y que el investigador conoce, de forma previa a la estimación, cuando ha tenido lugar (Stock y Watson, 2009). Sin embargo, a través de la metodología que en este segundo capítulo se propone, se pueden utilizar datos reales sin dar por sentado la presencia o la fecha en la que estas rupturas estructurales han tenido lugar. Esto se lleva a cabo usando la información contenida en el mismo conjunto de datos de 110 variables mensuales que es utilizada para la identificación de las posibles rupturas estructurales correspondientes con cambios en la interactuación de esas variables macroeconómicas. Una vez identificados estos momentos de ruptura, se permite a los parámetros del modelo variar dependiendo del comportamiento de los datos en el periodo en el que nos encontremos y, por tanto, responder de manera distinta a los cambios en la política monetaria en cada uno de esos escenarios.
La estimación de un modelo de estas características, en el que se permite evolucionar de manera distinta la dinámica de los factores que resumen los datos en cada escenario estructural identificado, entraña ciertas dificultades técnicas debido a que el número de parámetros a estimar crece proporcionalmente con el número de escenarios estructurales hallados en los datos mientras que, por otro lado, el número de observaciones temporales disponibles correspondiente con el total del periodo analizado ha de dividirse entre cada uno de dichos escenarios. Evidentemente, esto supone una reducción considerable del ratio entre la cantidad de observaciones y el número de parámetros a estimar que se traduce en un deterioro de la precisión de las estimaciones en el caso de que estas sean llevadas a cabo usando métodos convencionales. Por este motivo se recurre a métodos de estimación bayesianos que presentan una mayor precisión cuando este ratio entre el número de observaciones en la muestra y el número de parámetros es muy reducido. Aun apoyando el proceso de estimación en esta metodología, en estos modelos de gran tamaño, con muchas variables y en los que se permiten distintas dinámicas a lo largo del periodo analizado, se da una distribución posterior de los parámetros estimados por técnicas bayesianas con formas complejas y poco regulares. Por este motivo es necesaria la utilización de una metodología que permita la correcta selección de los valores iniciales para el proceso iterativo bayesiano que da lugar a esa distribución (Sims, Waggoner y Zha, 2008). Esto es llevado a cabo utilizando un método de optimización por bloques en el que el conjunto de parámetros a estimar es dividido en bloques atendiendo sus categorías y aplicando, iterativamente de un bloque a otro, una rutina de maximización de verosimilitud. Este proceso por bloques se ha mostrado como una manera más eficiente de incrementar la verosimilitud de los parámetros que la aplicación directa de esa rutina a todo el conjunto de parámetros directamente.

Una vez se aplica este proceso de estimación a los datos macroeconómicos para EE.UU en el periodo comprendido entre abril de 1974 y noviembre de 2013 se identifica la existencia de dos contextos estructurales: uno correspondiente con las etapas de recesión y alta volatilidad y otro más frecuente que tiene lugar durante las fases de expansión y baja volatilidad. Esta
clasificación del total del periodo analizado en dos escenarios distintos permite identificar cuáles son los datos más apropiados para la representación de las condiciones económicas actuales así como la estimación de reacciones de las 110 series incluidas en el conjunto de datos a cambios en los tipos de interés específicas para cada uno de esos dos escenarios. Estos resultados son comparados con aquellos que habrían sido obtenidos usando un Modelo de Factores Dinámicos de Gran Escala tradicional en el que la presencia de estas rupturas estructurales hubiese sido ignorada bajo dos posibles decisiones en cuanto a la muestra temporal que debe ser utilizada: unas calculadas con datos entre 1974 y finales de 2007 en las que se consideran que los últimos datos correspondiente con la etapa posterior a la crisis financiera no son representativos de la situación actual por su gran volatilidad; y otras utilizando toda la muestra representando en este caso la decisión de un investigador que se decanta por usar toda la información disponible. De la comparación de ambos resultados se observa como las Funciones de Respuesta al Impulso lineales (a aquellas que no se permiten cambios en los parámetros del modelo asumiendo una relación invariante entre las variables macroeconómicas) estimadas con datos previos a 2008 son muy similares a las estimadas con la metodología propuesta que corresponden a los periodos caracterizados por baja volatilidad. Por otro lado, también se observa que las Funciones de Respuesta al Impulso lineales basadas en datos que también incluyen el periodo de la Gran Recesión posterior a 2008 están condicionadas por la forma y magnitud de las Funciones de Respuesta al Impulso estimadas permitiendo cambios en los parámetros del modelo que se corresponden con periodos de más volatilidad. Esto muestra los efectos distorsionantes de estas últimas observaciones del periodo más volátil una vez son incluidas en un Modelo de Factores Dinámicos convencional.

De la clasificación de los diferentes periodos estructurales identificados mediante la implementación de la metodología propuesta en el segundo capítulo de esta tesis se desprende que la crisis de 2008 dio paso a un periodo de alta volatilidad y recesión pero que no tuvo efectos permanentes en la situación económica estructural del EE.UU. y como, tras unos
años, los patrones e interacciones macroeconómicas vuelvan al estado anterior al verano de 2008. Sin embargo, la situación monetaria actual de este país puede seguir considerándose como extraordinaria debido al elevado nivel de los agregados monetarios y unos tipos de interés oficiales que siguen en mínimos históricos y cercanos a cero. La cuestión empírica que se deriva de esta situación monetaria poco convencional en un momento en el que la economía real parece recuperada se centra en la identificación de la estrategia monetaria óptima que debe ser llevada a cabo por los bancos centrales en su regreso a un contexto monetario tradicional. El tercero de los capítulos de esta tesis se centre en esta cuestión.

La forma, magnitud y fechas de la retirada de los estímulos monetarios para la vuelta a una situación normal en el nivel intervención por parte de las autoridades monetarias debe hacerse teniendo en cuenta que una retirada precoz de los programas de estímulo podría frenar la actividad económica y el empleo en mayor medida de lo deseado mientras que una prolongación excesiva de estos estímulos generaría una mayor dependencia del sistema financiero de las inyecciones públicas de liquidez y, en último término, podría traducirse en fuertes presiones inflacionistas. Además, las recientes inyecciones masivas de liquidez y la bajada de tipos de interés a mínimos cercanos a cero no tienen precedentes en la historia reciente de las economías desarrolladas lo que añade incertidumbre sobre las consecuencias de la retirada de estas medidas excepcionales. El tercer capítulo de esta tesis sugiere una metodología basada en el uso de los Modelos de Factores Dinámicos de Pequeña Escala que puede ayudar a evaluar las consecuencias futuras de las decisiones tomadas por las autoridades monetarias en los principales indicadores macroeconómicos.

Las buenas propiedades predictivas de estos modelos se basan en su habilidad para incluir toda la información disponible en un determinado momento. Cada indicador macroeconómico presenta distintas fechas de publicación; esto supone, que en un determinado momento, haya información disponible para alguno de ellos para cierto mes o trimestre pero que para otro indicador sólo dispongamos de información hasta algún periodo anterior. Por este motivo el conjunto de información disponible en una determinada fecha presenta un final
irregular en el que tendremos ciertas observaciones mientras que el valor de otros indicadores aún no estará disponible para ese mismo periodo. Contrariamente a otras metodologías que requieren un conjunto de datos con un final regular, en el que se descartan las últimas observaciones de algunos indicadores para tener un conjunto de datos equilibrado al final de la muestra, los Modelos de Factores Dinámicos pueden incluir toda la información disponible en un determinado momento a través de una modificación en el proceso de estimación que permite distinguir que indicadores han sido publicados de los que no. Esta característica puede ser aprovechada por los responsables de la política monetaria como guía para la toma de decisiones. Para ello se propone incluir en el conjunto de información disponible para el público en general la evolución futura de una variable representativa de la política monetaria que es conocida únicamente por los mismos responsables de la política monetaria para la consecución de un determinado objetivo en el corto plazo como, por ejemplo, la trayectoria que deberían seguir los tipos de interés durante el próximo año para alcanzar niveles similares a los vigentes durante el periodo previo a la crisis financiera de 2008. Las predicciones que utilicen este conjunto de información estarán basadas por tanto en la evolución reciente de los indicadores incluidos en el modelo así como también de la evolución de las variables monetarias fijada por el banco central para el futuro. Por tanto, la evaluación de las consecuencias de la decisión de la autoridad monetaria acerca de la evolución futura de esa variable puede llevarse a cabo a través de un ejercicio comparativo de las predicciones basadas en esa decisión inicial obtenidas con el modelo con otras en basadas en una decisión alternativa como, por ejemplo, mantener los tipos de interés inalterados durante el próximo año. Esta comparativa permite valorar fácilmente las consecuencias de cada una de estas dos posibles decisiones de la política monetaria en la evolución de los indicadores incluidos en el modelo.

Sin embargo, en el actual contexto, la selección de los indicadores monetarios representativos de la postura de los bancos centrales entraña ciertas dificultades. Esto se debe a que los tipos de interés oficiales, el indicador utilizado tradicionalmente para esto fines, apenas
muestran variación desde finales de 2008 y, por tanto, dejan de tener contenido informacional ya que esta variable monetaria fue sustituida por las inyecciones de liquidez para seguir estimulando la economía una vez que los tipos de interés alcanzaron su mínimo en torno a cero. Igualmente, los agregados monetarios representativos de la cantidad de dinero en circulación carecen de variabilidad y contenido informativo antes de 2008. Para solucionar este aspecto se utiliza una medida sintética que resume ambos tipos de estímulos en un solo indicador que es sustitutivo de los tipos de interés ya que se le permite tomar valores negativos cuando lo tipos oficiales alcanzan su mínimo de cero. Este indicador, conocido como Shadow Rate, es calculado utilizado los tipos de interés futuros como medida de las expectativas de mercado sobre la evolución de los tipos oficiales a través de la información que disponible a cerca de las inyecciones de liquidez y las declaraciones de los bancos centrales sobre la duración de las medidas excepcionales. La literatura previa (Wu y Xia, 2014) ha mostrado como estos indicadores monetarios sintéticos presentan una relación con las variables macroeconómicas durante los periodos en los que toman valores negativos equivalente a la relación que tradicionalmente ha habido entre las variables macroeconómicas y los tipos de interés oficiales cuando estos no se encontraban en su mínimo.

En el caso concreto de este capítulo se valoran cinco posibles sendas de este indicador sintético que podrían ser seguidas por la Reserva Federal de EE.UU. y se realiza una predicción futura del Producto Interior Bruto, un indicador de empleo, de ventas, producción industrial, ingresos y precios para cada una de estas posibles sendas. De su comparación se desprende en qué medida una política monetaria expansiva seguiría estimulando el rendimiento económico mientras que una contractiva reduciría las tasas de crecimiento de estos indicadores de actividad y empleo. Por otro lado, la evolución de los precios apenas se vería alterada bajo la implementación de estas distintas sendas resultado, este último, consistente con las escasas subidas de precios que siguieron a la implementación de la extraordinaria batería de estímulos monetarios que se han puesto en práctica tras la crisis financiera de 2008.

Así pues, a lo largo de los tres capítulos de esta tesis se muestra como los Modelos de
Factores Dinámicos son una herramienta con un gran potencial para el análisis de la política monetaria así como para representar, evaluar y predecir la evolución económica incluso bajo restricciones en la disponibilidad de datos como las que se dan en países desarrollo. En esta tesis se ofrecen resultados que, basados en la gran cantidad de datos que puede incluirse en estos modelos, muestran como la crisis financiera de 2008 dio lugar a cambios en las interacciones macroeconómicas y a la presencia de un escenario estructural distinto al de los años previos que habían estado caracterizados por una baja volatilidad y largos periodos de expansión. La identificación de estos cambios en los patrones y relaciones macroeconómicas requiere la implementación la nueva versión de los Modelos de Factores Dinámicos aquí propuesta. Esta versión permite capturar dichos cambios así como diferenciar las distintas consecuencias, mecanismos de propagación y magnitud de los efectos de la política monetaria para cada uno de esos contextos estructurales. Por último, propone la aplicación de los Modelos de Factores Dinámicos para valorar las consecuencias de varias posibles estrategias monetarias en la evolución futura de un conjunto de indicadores macroeconómicos clave a fin de determinar la estrategia óptima de regreso a una situación monetaria similar a la que se daba con anterioridad a la crisis financiera de 2008.
Chapter 1

Forecast Accuracy of Small and Large Scale Dynamic Factor Models in Developing Economies

1.1 Introduction

The information contained in some key macroeconomic aggregates is of crucial relevance for economists. They provide a general assessment about the performance of a given economy, allowing to construct expectations about other specific indicators and to evaluate the results of the strategies deployed by policy makers and central bankers.

The current situation of global uncertainty, the increasing differences in the economic achievement between emerging countries with respect to developed economies and the different trends regarding fiscal and monetary policy in countries with low or negative growth all stress the relevance of early evaluation of such indicators in real time.

Unfortunately, the burdensome accounting task needed for the computation of these key
aggregates causes a considerable delay in the release of the data. Let us consider Gross Domestic Product (GDP) as the main indicator of the current economic situation. It is usually published at a quarterly frequency and released with more than two months of delay. However, there are hundreds, or even thousands of more specific indicators that require an easier computation, which are earlier released at a higher frequency.

Dynamic Factor Models (DFMs) take advantage of this increasing availability of data. Given that macroeconomic series are very collinear, it is assumed that they can be decomposed in two orthogonal parts: a reduced set of latent common factors which capture the most of the comovements in the data and an idiosyncratic component that only affects a specific series or a reduced set of them. Besides other applications, this factor decomposition has been implemented with forecasting purposes. Because of the lower number of factors with respect to the amount of available data, factors can be included in a forecast equation for a targeted variable, as GDP, with a reduced set of regressors containing the relevant information while keeping a parsimonious specification.

Recent literature has shown a clear improvement in short term forecasting by using DFM s. They have become a key tool for several public institutions such as the European Central Bank and Federal Reserve among others. However, DFM s have been previously treated separately by two clearly distinguishable streams of literature. Small Scale DFM s (SS-DFM s) where the common factor is estimated from a reduced set of indicators considered as representative of the whole economy or prescreened by the forecaster under some technical criteria and a second type of models known as Large Scale DFM s (LS-DFM s) where factors are estimated from a huge dataset under the premise that there is no reason to discard any information. Depending on the number of series used for the estimation of the factors these two DFM s present different theoretical assumptions, computational limitations and estimation procedures. This paper tries to determine which is the more adequate of these approaches for short-term prediction of GDP. The main characteristics of both methodologies are reviewed next.
1.1. **INTRODUCTION**

The paper by Stock and Watson (1991) is considered as a pioneer work in the application of SS-DFMs. They compute a single factor as an alternative to the Index of Coincident Economic Indicator compiled by the Department of Commerce of the US with a small dataset composed by four macroeconomic monthly series related with demand, supply, employment and income. This initial methodology has been extended by the inclusion of indicators in different frequencies. Mariano and Murasawa (2003) add quarterly GDP to this initial set of indicators for the computation of a latent monthly GDP. Aruoba, Diebold and Scotti (2009) include series at weekly and daily frequency for the estimation of an indicator of the economic activity in continuous time. Camacho and Perez Quiros (2010) combine monthly data with several quarterly early estimations of GDP for the short-term forecast of the euro area GDP growth.

Because of the reduced cross section dimension of the datasets used in these models, the common factor and its loadings are both simultaneously estimated by maximum likelihood via the Kalman filter. However, the number of parameters to be estimated rises considerably with the number of indicators included. Thus, for computational reasons, this technique is able to process a limited amount of series. Moreover, in these models, the part of each series not explained by the factor, the idiosyncratic component, is assumed as non cross-correlated. Obviously, this assumption difficultly holds to the extent to which the number of included series increases. Accordingly with the classification of Chamberlain and Rothschild (1983), models relying on this assumption are known as *exact factor models*.

Because of these caveats, another stream of the literature has recently focused on the LS-DFMs. With a different estimation strategy, these models are able to deal with a bigger amount of indicators and limitations regarding the cross section dimension of the dataset are avoided. Furthermore, the thick assumption about zero cross correlation of the SS-DFMs is relaxed allowing for some degree of cross correlation between the idiosyncratic terms (*approximate factor models*).

A seminal work in the application of this procedure for macroeconomic forecast is Stock
1.1. INTRODUCTION

and Watson (2002). Giannone, Reichlin and Sala (2004) added to this model a second
equation, which specifically characterizes the law of motion of the factors; the innovations
of this second equation were successfully related with nominal and real shocks in the US
economy. Rünstler et al. (2009) find that this method outperforms prediction based on
quarterly data or bridge equations. Giannone, Reichlin and Small (2008) and Angelini et al.
(2011) carry out short term forecast of the GDP growth of the US and euro area respectively.
Doz, Giannone and Reichlin (2011) show the consistency of this procedure under weak cross
correlation of the idiosyncratic component when cross section and time dimensions of the
panel tend to infinity.

Unfortunately, this model is not free of drawbacks. The theoretical conditions under
which consistency is achieved may be unrealistic in empirical applications with real data.
Indeed, Stock and Watson (2002b) find some worsening of the model when the idiosyncratic
component presents large serial correlation. Boivin and Ng (2006) point out that the amount
of the time series included in the model is not harmless; in order to satisfy the theoretical
requirements for consistency of large cross section dimension, forecasters put together all
the available information. Up to some point, this may be in direct conflict with the other
theoretical requisites about weak idiosyncratic cross correlation; it is because by adding more
series to the panel it is more likely to find series belonging to the same broad category which
are highly correlated. According to this, Bulligan, Marcellino and Venditti (2012) point out
that there might be practical cases where a large number of variables are not sufficient to
consider the influence of the idiosyncratic components negligible.

On the other hand, regardless the increasing relevance of developing economies in the
global economic scenario, DFM s have been almost uniquely evaluated in advanced economies
as the US or EU countries. Clearly, implementation of DFM s in developing countries entails
some difficulties since they present more abrupt macroeconomic transitions and constraints
in data availability such as lower amount of time series, usually shorter or with missing values
in many cases.
To the best of my knowledge, only two articles have applied DFM s for developing economies in the particular case of Latin American countries: Liu, Matheson and Romeu (2012) find a better performance of a LS-DFM at GDP forecasting with respect to other multivariate autoregressive models at quarterly frequency or bridge equations with monthly series for ten Latin American countries and Camacho and Perez Quiros (2011) compute a monthly latent factor for six of those countries with a SS-DFM which, also provides better predictions for GDP than autoregressive specifications.

Unfortunately, up to now, previous literature has not investigated which is the more adequate approach in a real context. As stressed by Aruoba, Diebold and Scotti (2009), a comparative assessment of these two techniques from an empirical perspective is necessary despite the theoretical limitations of both methodologies.

Alvarez, Camacho and Perez Quiros (2012) carry out a first comparison between the two DFM s controlling for the characteristics of the data with Monte Carlo simulations. They find that the SS-DFM outperforms the LS-DFM when the panel contains oversampled categories or with high serial correlation of the idiosyncratic component. As an additional support of their findings based on simulated data, both factor models are applied to a balanced dataset for the US economy between 1959-1998 to forecast two real and two nominal monthly indicators. The real variables were similarly or better predicted in many cases by the SS-DFM. Nominal variables were always more accurately forecasted by the SS-DFM.

The main contribution of this paper is to extend this initial work in three ways:

First, in order to assess the external validity of these previous findings, the forecast accuracy of LS and SS DFM s is compared from a completely empirical point of view. Both DFM s are put at work in a real context through six datasets with actual series from different countries, which are expected to presents heterogeneous characteristics. The selected countries are those Latin American countries commonly analyzed in Liu, Matheson and Romeu (2012) and Camacho and Perez Quiros (2011): Argentina, Brazil, Chile, Colombia, Mexico
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and Peru. In this way, models are tested in a context of economic volatility and limitations in the accessible data. These characteristics, common in developing economies, are crucial in the evaluation of the precision of DFMs at short term forecasting because factors have to be estimated from indicators reflecting sharp macroeconomic changes and also because of the small amount of data at hand.

Second, due to its relevance as aggregate macroeconomic indicator, instead of other monthly series with more particular information, the selected variable to be forecasted in this paper is quarterly GDP growth. In order to take advantage of the large amount of specific series available at a monthly frequency for the prediction of GDP, the implementations of the models is carried out with mixed frequencies where the monthly estimations of the latent factors have to be related with quarterly rates of GDP growth through aggregation rules.

Finally, the treatment of the data used every month for the prediction of quarterly GDP growth is considered from a realistic point of view. I develop a pseudo real time out-of-sample forecast exercise where the actual situation faced by the forecaster in terms of data availability is closely reproduced: taking into consideration the calendar of the releases for the indicators in the datasets for each country, every month within the out-of-sample forecast period, panels are updated including all the observations which were already published at that date; once updated, dataset differs for the actual series released at that time because they do not include changes due to data revisions. Because of the differences in the publication lag within the set of indicators, models are modified following Giannone, Reichlin and Small (2006) and Camacho and Perez Quiros (2010) in order to deal with unbalanced panels. Based on all the information published for a given month, I predict the previous quarter rate of growth of GDP which is going to be released in the current quarter, nowcast, and quarterly rate of growth of GDP corresponding with the following release in the next quarter, forecast. Results will show a general improvement in the precision of the estimates along the quarter, especially at nowcasting. This highlights the relevance of the inclusion of the latest released data, especially at short-term prediction, with respect to out-of-sample
1.2   THE MODELS

forecast based on balanced panel where useful information is discarded.

After the evaluation of both models for a sample of six developing economies, I find that
the LS-DFM provides more accurate predictions for the Argentinean GDP at nowcasting
and forecasting. On the contrary, in the case of Peru, it is the SS-DFM the model which
presents best results for the two temporal horizons.

For Brazil and Mexico nowcasted GDP presents lower RMSE when computed by the LS-
DFM while the one quarter ahead forecast is more accurate under the SS-DFM approach.
The opposite happens in Colombia where the SS-DFM provides more accurate nowcast and
the LS-DFM is better at forecast. Finally, the performance of SS and LS DFMs is very
similar in the case of the Chilean GDP.

These mixed results suggest that DFMs should be evaluated taking into consideration
their theoretical assumptions but also knowing that none of these limitations are sufficiently
unrealistic in order to discard one model in favor of the other when they are applied in an
empirical framework.

The remaining of the paper is organized as follows. The next section presents the char-
acteristics of the SS and LS DFMs. Section 3 describes the dataset and the details of the
pseudo real time out-of-sample experiment. Section 4 includes the empirical results. Section
5 concludes.

1.2    The Models

Define \( y_t \) as our quarterly aggregate of interest to be forecasted and \( x_t \) as a set of \( n \) macroeco-
nomic series expressed in a monthly basis and earlier released than \( y_t \). Obviously, monthly
and quarterly macroeconomic data are related thus, by taking advantage of such a relation-
ship, one can project the quarterly aggregate on the monthly data once it is available.
1.2. THE MODELS

Regardless their different frequencies, the simple OLS regression of \( y_t \) on \( x_{it} \) with \( i = 1, \ldots, n \) becomes inefficient when the number of monthly predictors, \( n \), is big enough. Moreover, the number of regressors will increase dramatically if the forecast equation includes lags of the explanatory variables.

However, let us consider that the whole economy is driven by a reduced number of unobserved shocks. Under this premise, DFMs assume that series can be decomposed into two orthogonal parts accordingly with the following equation:

\[
x_{it} = \lambda_1^1 f_1^t + \ldots + \lambda_r^r f_r^t + \varepsilon_{it} \tag{1.1}
\]

Where \( f_1^t, \ldots, f_r^t = F_t \), with \( 1 \leq r < n \), is the set of latent factors which explain the most of the variation across the \( n \) predictors; \( \lambda_1^1, \ldots, \lambda_r^r = \Lambda_t \) are the factor loading for series \( i \) and the product of both, factors and loadings, is known as the common component. Finally, \( \varepsilon_{it} \) is the idiosyncratic component which specifically affects series \( i \) and might be serially correlated itself. In turn, the latent factors are also assumed to present an autoregressive dynamic of degree \( p \).

Thus, if the forecaster is able to estimate these latent factors, they can be included in a forecast equation, as a summary of the relevant information, while preserving a parsimonious specification.

A crucial issue is to distinguish whether the relevant information for the computation of the latent factors is contained in some determining series or it is better subtracted for a large set of data. Depending on this decision, the cross section dimension of \( x_t \) will vary and the estimation procedure will present different features. The next two subsections outline the details of both approaches.
1.2. THE MODELS

1.2.1 Small Scale Dynamic Factor Model

The SS-DFM analyzed is based on the single factor model of Stock and Watson (1991) where four monthly series, considered of relevance because of its relationship with demand, supply, employment and income, are used for the estimation of the common factor. As in the refined version of Camacho and Perez Quiros (2010), this initial set of indicators is enlarged with quarterly GDP, soft indicators due to its early release and variables which represent specific features of each country. Depending on the kind of each of those indicators they will be related with the unique monthly latent factor in a different way.

GDP is released at a quarterly frequency. Following Mariano and Murasawa (2003), it can be shown that the quarterly rate of growth of a given variable \( z^q \) is related with its monthly rate of growth \( z^m \) through the following expression:

\[
    z^q = \frac{1}{3} z^m_t + \frac{2}{3} z^m_{t-1} + z^m_{t-2} + \frac{2}{3} z^m_{t-3} + \frac{1}{3} z^m_{t-4}.
\]

Thus, the quarterly rate of growth of GDP \( y^q \) observed at the last month of each quarter will be related with monthly factor \( f \) in such a way. Hard monthly series are introduced in annual growth rate \( (x^h) \); therefore, they will depend on the sum of the twelve last monthly growth rates of the factor. Soft indicators (surveys) will be included in level \( (x^s) \), however they are also assumed to present the same twelve month lag dependence.

Taking into consideration the factor decomposition described in equation (1) for a single factor \( (r = 1) \) and the different relationship of the monthly factor with each type of indicator, the main equations of the model are summarized as follows:

\[
\begin{pmatrix}
    y^q_t \\
    x^m_{t1} \\
    \vdots \\
    x^m_{tns}
\end{pmatrix} = \begin{pmatrix}
    \beta_y \left( \frac{1}{3} f_t + \frac{2}{3} f_{t-1} + f_{t-2} + \frac{2}{3} f_{t-3} + \frac{1}{3} f_{t-4} \right) \\
    \beta_1 \sum_{j=0}^{11} f_{t-j} \\
    \vdots \\
    \beta_{ns} \sum_{j=0}^{11} f_{t-j}
\end{pmatrix} + \begin{pmatrix}
    U^q_{yt} \\
    u_{1t} \\
    \vdots \\
    u_{ns+1}
\end{pmatrix}
\]
where \( U_{yt} = \frac{1}{3} u_{yt} + \frac{2}{3} u_{yt-1} + u_{yt-2} + \frac{2}{3} u_{yt-3} + \frac{1}{3} u_{yt-4} \) and \( x^n_1, ..., x^n_m \) represents the whole set of soft and hard monthly indicators \((x^h, x^s)\) of size \(n^s\).

The dynamic of the latent factor and the idiosyncratic components are also specifically characterized:

\[
\begin{align*}
   f_t &= \phi^f_1 f_{t-1} + \ldots + \phi^f_a f_{t-a} + \epsilon^f_t \quad (1.3) \\
   u_{yt} &= \phi^{uy}_1 u_{yt-1} + \ldots + \phi^{uy}_b u_{yt-b} + \epsilon^{uy}_t \quad (1.4) \\
   u_{1t} &= \phi^{u1}_1 u_{1t-1} + \ldots + \phi^{u1}_c u_{1t-c} + \epsilon^{u1}_t \quad (1.5) \\
   &\vdots \\
   u_{ns_t} &= \phi^{u ns}_1 u_{ns_t-1} + \ldots + \phi^{u ns}_d u_{ns_t-d} + \epsilon^{u ns}_t \quad (1.6)
\end{align*}
\]

Finally, \( \epsilon^f_t, \epsilon^{uy}_t, \epsilon^{u1}_t, \ldots \) and \( \epsilon^{u ns}_t \) are assumed to be independent and identically normal distributed with zero mean and their covariances assumed to be zero.

Let be \( Y_t = (y_t, x^h_t, x^s_t) \) a vector which collects observed data at period \( t \) and \( S_t \) the state vector equal to

\[
(f_t, f_{t-1}, \ldots, f_{t-11}, u_{yt}, \ldots, u_{yt-5}, u_{1t}, u_{1t-1}, \ldots, u_{ns_t}, u_{ns_t-1}).
\]

With the necessary definition for the matrices \( \Lambda \) and \( A \), equations (2) to (6) can be included in following the state space representation:
1.2. THE MODELS

\[ Y_t = \Lambda S_t + w_t \]  \hspace{1cm} (1.7)

\[ S_t = AS_{t-1} + v_t \]  \hspace{1cm} (1.8)

Because of this representation of the system, the latent factor and parameters can be estimated by maximum likelihood using the Kalman Filter.

Due to the different publication lags of the series the panel presents a “ragged end” where some series are available while others are missing for a given month at the end of the sample period. In order to include all the possible information, the filter is modified to give no weight to missing observations while including the latest releases. It is done by avoiding the part of the Kalman gain matrix which corresponds to these missing observations in the update equation. Besides, the factor and the nowcast and forecast of the targeted variable can be easily projected by extending the end of the panel with missing observations.

1.2.2 Large Scale Dynamic Factor Model

The LS-DFM corresponds with the model of Doz (2011) where the factors are estimated in two steps.

Let us consider the \( T \times n^L \) matrix \( X_T \) as a set of monthly data which includes \( n^L \) macroeconomic series from moment 1 to \( T \) and where \( n^L >> n^s \). Under the assumption that these observed data can be decomposed into a common component that captures the bulk of the comovements in a given economy and a idiosyncratic part which affects only a single or a small set of series the model can be directly set in a state space representation:
1.2. THE MODELS

\[ X_t = \Lambda F_t + \xi_t \] (1.9)

\[ F_t = \sum_{s=1}^{p} A_s F_{t-s} + B \eta_t \] (1.10)

\( F_t \) represents the \( r \times 1 \) vector of common factors with \( r \geq 1 \) for a given period \( t \). They are contemporaneously related with the \( n^L \) observed series of \( X_t \) at the same period through the \( n^L \times r \) matrix of loadings \( \Lambda \). The idiosyncratic component \( \xi_t \) follows a \( N(0, \psi) \) distribution; its potential serial correlation is not specifically characterized since \( \xi_t \) becomes negligible as cross section dimension increases. The second equation represents the law motion of the common factors where they are related with their \( p \) lags via the \( r \times r A_s \) matrices with \( s = 1, \ldots, p \). Innovations of equation (10) are driven by the set of \( q \) dynamics factors \( \eta_t \). The number of the contemporaneous (static) factors, \( r \), is bigger or equal than the number of dynamics factors, \( q \), because \( F_t \) consists of current and lagged values of the of the dynamic factors \( \eta_t \). This is known as the static representation of the DFM (see Bai and Ng, 2007, for further description). Thus, \( \eta_t \) is loaded by the full rank \( r \times q \) matrix \( B \). Finally, \( \eta_t \sim N(0, I) \).

Due to the different dates in which series are released the panel of data \( X_T \) is unbalanced and presents a “ragged end”. However, due to large cross section dimension of the panel data, MLE is not directly applied to the equations (9) and (10) via the Kalman filter for the inclusion of the most recent data. Instead the estimation procedure is carried out in two stages. First, the \( r \) factors \( \tilde{F} \) are obtained by Principal Components Analysis (PCA) from the balanced panel of monthly data. Then, the OLS regression of \( X \) on \( \tilde{F} \) gives the estimates \( \tilde{\Lambda} \) and \( \tilde{\psi} \) and the regression of \( \tilde{F} \) on its \( p \) lags gives \( \tilde{A}_1, \ldots, \tilde{A}_p \). \( \tilde{B} \) is estimated applying PCA to the covariance matrix of the error term of the VAR. The second stage provides
a reestimation, \( \hat{F} \), of the factors: given that the model has a state space representation, the Kalman smoother can be directly applied to the entire unbalanced panel assuming that the matrices linearly estimated in the previous step (\( \hat{\Lambda}, \hat{\psi}, \hat{A}_1, \ldots, \hat{A}_p \) and \( \hat{B} \)) are the correct matrices. Finally, as in the SS-DFM, the filter is modified giving no weight to the missing observations in the update equation.

The forecast equation for a given target variable, GDP in this case, is based on the projection of the factors obtained in the previous part. However, GDP is observed at a quarterly frequency and each of the \( r \) estimated factors \( f_t \) are obtained from the monthly data. In order to express them at a quarterly frequency, they are transformed, as in Rünstler et al (2009) or Angelini et al. (2011), by the following aggregation rule:

\[
    f_t^Q = \frac{1}{3}(f_t + f_{t-1} + f_{t-2})
\]

This aggregation rule requires to transform the data in 3-months differences or in 3-month differences of the logarithms. Due to this differentiation, the quarterly aggregates of the monthly factors \( f_t^Q \) represent a three month rate of growth and the forecast equation is consequently defined as:

\[
    y_t^Q = \hat{\alpha} + \hat{\beta} f_t^Q
\]

where, in our case, \( y_t^Q \) is the quarterly rate of growth of GDP and \( \hat{\alpha} \) and \( \hat{\beta} \) are estimated by OLS.
1.2. THE MODELS

Contrary to the SS-DMF where the number of factors is fixed and equal to one due to the technical limitations of its estimation procedure, in the case of the LS-DFM there is uncertainty about the optimal number of factor that must be extracted from the observed data.

The most popular method among practitioners for the selection of the correct number of factors, $r$, is the information criteria proposed by Bai and Ng (2002). Nevertheless, and as highlighted by Caggiano, Kapetanios and Labhard (2011), this approach is designed in order to determine the optimal amount of factors to summarize a large dataset without take into consideration whether all those factors are relevant for the forecast of a target variable $y_t$. Thus, following these authors, several specification criteria were evaluated paying attention to their results in the forecast equation (12) instead of to their ability for the description of the explanatory data.

Although the results are broadly similar, the criterion developed by Bai and Ng (2002) produces higher errors in equation (12) since it tends to choose too many factors given the short temporal dimension of the panel. The Bayesian criterion proposed by Stock and Watson (1998) includes a penalty function which has to be minimized jointly with the Mean of the Square Errors of the forecast equation and leads to lower values of $r$. However, the number of factors was finally recursively determined such that the Root Mean Square Error (RMSE) of the forecast equation is minimized since results were slightly better under this procedure. Lag length for the state equation, $p$, and the number of pervasive shocks, $q$, were marginally selected for each value of $r$ using the Schwartz Information Criterion and the criterion proposed by Bai and Ng (2007) respectively. This iterative process was repeated in each out of sample period using only information available at that date as explained in the next section.
1.3 Data and Pseudo Real Time Out-of-Sample Exercise

The aim of the models is the nowcast and short term forecast of GDP growth rate based on the last available monthly information. However, the publication lag of monthly series differs depending on their categories. Soft and financial indicators are usually earlier released than hard indicators. Due to these discrepancies, the dataset presents a “ragged end” with some observations available while other are missing for a given month at the end of the sample. Moreover, the relevant information for the prediction exercise evolves every month within the quarter to the extent in which new monthly series are released. Obviously, the latest released data will play an important role in the nowcast and forecast accuracy and they must be considered for the assessment of the models. In order to closely mirror the actual availability of data faced by the forecaster in a real-time situation, this changing dataset is replicated every month. This exercise only differs for the actual real time context because the panel does not take into consideration data revisions.

The data were downloaded on November 22nd of 2011. The pattern on the data availability on that date due to the differences in the publication lags for each series is replicated every month within the quarter across the out-of-sample forecast period. Let be $X_T$ the observed data at the end of the sample period $T$. At that date each monthly series $x_i$ presents its last observation for a month $T - h_i$, where $h_i$ represents the publication lag for series $i = 1, \ldots, n$. Hence, for any month $t$ of the out-of-sample nowcast and forecast exercise, the last observation of series $i$ which will be included corresponds with month $t - h_i$. Thus, the “ragged end” of the dataset used for the estimations every second month of a given quarter will be equal to the pattern observed in November 2011. For the first and third months of every quarter the availability of monthly series will present the same shape while quarterly series include in the dataset of the SS-DFM or in the forecast equation of the LS-DFM will be observed according to their release date within the quarter.
The data were downloaded from Datastream, central banks and offices of statistics of the six analyzed countries. Table 1 briefly classifies the series in seven categories for each country: those series labeled as key monthly indicators by Datastream, activity, trade, salaries and employment, financial, prices and surveys.

Because of the different characteristics of the models, the number of series included in each of them varies. While the LS-DFM includes all the available information in order to satisfy assumptions regarding large cross section and time dimension, the SS-DFM includes a considerably smaller subset of indicators within those contained in the LS-DFM.

Selection of the variables for the SS-DFM is based on Camacho and Perez Quiros (2011). The dataset for each country begins with four indicators as in the basic model of Stock and Watson (1991): industrial production as representative of the general level of production, a sales series for supply, an indicator for the evolution of income and one last indicator for employment. This initial group is enlarged with GDP, a soft indicator about expectations due to its early release, imports and export series to control for the effect of international trade and some specific indicators considered of relevance to capture the particular characteristic of this country or its interdependence with other countries. Following this procedure, series with a factor loading with sign opposite to the expected, non significant indicators or those which reduced the percentage of the variance of the GDP explained by the common component were discarded. Table 2 contains the subset of variables selected for each country under these criteria.

In order to keep this research in line with previous applications in the literature corresponding with the LS and SS DFMs, frequency and interval for the rate of growth of the unobserved factors are distinct in each model. As a consequence, the differentiation of the data and the computation of its quarterly aggregates are carried out in a different manner.

Moreover, this different frequency and interval of the factors used in the previous literature of these two models have some advantages in the particular context of this paper. In
the LS-DFM, monthly indicators are introduced in the panel in three month differences as in the papers mentioned above. Accordingly with this transformation, the panel provides the three month rate of growth of the quarterly latent factors once it is aggregated through equation \((11)\). By taking differences with respect to the previous quarter, instead of to the previous year, one is able to save some observations. This becomes a crucial issue given the high constraints in the availability of data for developing economies. Notice that the first step in the estimation strategy of the LS-DFM requires a balanced panel for the application of PCA where temporal dimension of the panel is reduced by eliminating the observations in the "ragged end". Later on, in the forecast equation, the latent factors estimated for each month are transformed into their quarterly aggregates dividing by three the temporal dimension of the observations that will be the regressors for quarterly GDP. For these reasons, the LS-DFM is more affected by the short availability of data and the three-months differentiation is more suitable in this model.

In the SS-DFM, due to the smaller cross section dimension of its dataset, \(n^*\), there is no need of balanced panel since the Kalman Filter is directly applied without previous steps and monthly variables are related with quarterly indicators without split the temporal number of observations. Thus, monthly data is introduced in twelve differences and related to the single latent factor through equation \((2)\) as in Camacho and Perez Quiros (2011) with smaller consequences in the available degrees of freedom. Under this procedure, this model estimates the monthly rate of growth of a monthly factor.

Panel data is updated every month, the parameters of the models and selection criteria are reestimated considering the new arrivals of data and factors are newly projected ahead for the nowcast and forecast of GDP growth.

The out-of-sample exercise starts in September 2009. Decision about this starting date was made judgmentally according to the data availability in each country in order to guarantee a large enough temporal dimension of the panel at the beginning of this exercise.
Due to its publication lag, the GDP of the third quarter, from July to September, will not be published until the end of the fourth quarter. At that date, September, a prediction for the quarterly rate of growth of GDP for the third quarter will be computed based on the available information in this month. Following the notation of Liu, Matheson and Romeu (2012), this projection corresponding with the next release of GDP is called Nowcast 1. With the same information set, the quarterly rate of growth of the GDP for the fourth quarter, which will be released in the next quarter, is also predicted (Forecast 1). These projections are repeated every month of the out-of-sample period corresponding with the end of a quarter reproducing the scheme depicted in the Figure 1.1.

In the next month, October, the estimation for the rate of growth of GDP for the third quarter which will be released in the current quarter (Nowcast 2) and the rate of growth of GDP for the fourth quarter which will be released in the next quarter (Forecast 2) are computed again based on the new set of information available till this month. Nowcast 2 and Forecast 2 will be computed again every month next to the end of each quarter as described in Figure 1.2.

Analogously, Figure 1.3 shows the Nowcast 3 and the Forecast 3 corresponding with the releases of GDP in the current and next quarters which are computed with the information set available two months after the end of the previous quarter.

1.4 The models at work

The aim of this paper is to empirically determine the best model for prediction of GDP growth given the intrinsic characteristics and data availability of the six considered economies. This analysis is carried out for several temporal horizons in order to control for the different pattern in the flow of data arrivals in each country. For this purpose, the RMSE of the nowcast and one quarter ahead forecast of GDP growth is computed for every month within
1.4. THE MODELS AT WORK

the quarter.

Table 3 contains the results for the Large and Small Scale DFMs. To simplify comparisons, the RMSE of the models are presented as a ratio over the RMSE of a benchmark model. This model is an Autoregressive model for quarterly GDP growth with $p \leq 4$ lags selected by Schwartz Info Criterion. Since GDP is observed at a quarterly frequency, the nowcast and forecast of this model will be the same during the three months of the quarter. First column of Table 3 presents the RMSE of the AR($p$) model for the six countries. The next three couples of columns represent the ratio of the RMSE of the SS-DFM and the LS-DFM over the RMSE of the benchmark model for first, second and third month of each quarter respectively. Thus, an entry lower than one means that the DFM outperforms the AR($p$). The last two columns contain the average of the nowcast and forecast relative RMSE of the three months for each country. Notice that the entries for the nowcast corresponding to the third month of Chile are empty. It is because GDP is earlier released in this country and for the date in which third nowcast is computed Chilean GDP is already published.

Factor models based on monthly data clearly outperform the autoregressive benchmark model for quarterly GDP at nowcasting. Exceptionally, the AR($p$) provides a lower RMSE for Colombia than for the other five countries. In fact, the results of this benchmark model in this country are only beaten by the SS-DFM in the third month of the quarter. As expected, the errors of the predictions for the GDP which will be published in the current quarter show an overall decrease with the arrival of new data from month to month within the quarter. However, this pattern is less clear for the next quarter ahead forecast. These findings highlight the relevance of the informational content of new releases and its important role in short term prediction.

Accordingly with the relative RMSE of both models applied to Argentinean economy, the LS-DFM presents higher accuracy than the SS-DFM at nowcasting GDP growth during the first two month of the natural quarter (Nowcast 2 and 3). It is during the last month of the quarter (Nowcast 1) when the SS-DFM presents lower errors. However, the average
for the relative RMSE of three months remains lower for the LS-DFM. Regarding the one quarter ahead projection of GDP growth (Forecast 1, 2 and 3), it is also the LS-DFM the model which presents a better performance during the three months of the quarter.

For the case of Brazil, the LS-DFM also has the best achievement at nowcasting in every month. Nevertheless, in the forecast at larger horizon, the SS-DFM produces the most accurate estimations at the beginning of each term (Forecast 1 and 2) while the model based on a large dataset of indicators is outperformed by the AR model.

Results corresponding with Chile are mixed. The LS-DFM is more precise than the SS-DFM in the first nowcast while the opposite happens in the second. However, these differences are very small and the averages relative RMSE are almost identical. For the one quarter ahead forecast, the single factor model beats the LS-DFM in the first two projections and presents a clear deterioration in the third forecast. On average, the differences in this case are also small and do not point out a clear winner between both approaches. It is important to notice that standard tests for statistical significance in the differences of the forecast based on each model, as Giacomini and White (2006), are not applicable to these results due to the reduced out-of-sample size. Recall that, because of the small temporal dimension of some series, the starting point for the out-of-sample evaluation of the models was fixed in September 2009. This allows us to produce 8 nowcast and 7 forecast predictions of quarterly GDP until November 2011, date when the dataset was downloaded.

Regarding Colombia, the AR model presents considerably better estimations in comparison with its results for the others five countries. In fact, none of the factor models are able to defeat this naïve model with the exception of the LS-DFM which presents better results in the one quarter ahead projections. Despite its simplicity, forecasts based on AR models have been shown to be rather accurate in previous literature. As highlighted in the results based on simulated data of Banerjee Marcellino and Masten (2008), this simple model may outperform DFM's, especially when the number of factors is large and the temporal dimension small.
1.5. **CONCLUDING REMARKS**

Similarly to the results for the Brazilian economy, the nowcast is better estimated during every month by the LS-DFM with data from Mexico. In this case the differences between the RMSE are considerably larger. The RMSE of the multi-factor model is approximately one half of the RMSE corresponding to the SS-DFM. Contrary, it is the single factor model the approach that provides the highest accuracy for the forecasts in every month of the quarter.

Finally, for the projection of Peruvian GDP growth, the SS-DFM presents the lowest RMSE for both nowcasting and forecasting while the model based on the large dataset only outperforms the AR model at nowcasting.

### 1.5 Concluding Remarks

This paper provides a comparative assessment of the short-term forecast performance of Small Scale and Large Scale Dynamic Factor Models in an empirical framework. From a cross-country dataset for six developing economies, quarterly growth rate of GDP is predicted every month within the quarter with monthly data released up to each month. In order to closely replicate the information set available for the forecaster, the arrival of data is carefully reproduced considering the publication lag for each series. This out-of-sample pseudo real time exercise uniquely differs for actual forecast that would be made every month because it does not include changes in the series due to data revisions.

Forecast is carried out for two different temporal horizons. A prediction for the immediately following publication of quarterly GDP which will be released, *nowcast*, and a second estimation for next quarter release, *forecast*. Both, nowcast and forecast RMSEs are compared for six Latin American countries.

Factor models based on monthly data show a better performance at the short-term forecast than autoregressive models with quarterly releases of GDP. In addition, the inclusion of the latest available data also improves the accuracy of the models month by month along
1.5. CONCLUDING REMARKS

the quarter.

Within the set of the six analyzed countries, both models present very similar results applied to data from Chilean economy. For the Brazilian, Colombian and Mexican economies, it seems that none of the limitations of one model prevail over the other. In fact, in all these three countries, there is a model that performs better than the other for a given temporal horizon of the projections. The most remarkable case is the nowcast of Mexico where the RMSE of the LS-DFM is around a half of the SS-DFM’s RMSE. This suggests that SS and LS DFMs should be complementarily applied in these economies depending on whether the target is the nowcast or the forecast of GDP growth. In the case of the Peruvian economy, both nowcast and forecast are better produced with a single factor computed by a SS-DFM based on a smaller set of reasonably prescreened series. On the other hand, the Argentinean GDP growth is better nowcasted and forecasted by the factors obtained from the large dataset.

LS-DFMs have recently received growing attention because of their capacity to summarize huge amount of information and also because these models relax the strong assumption of SS-DFMs regarding zero cross correlated idiosyncratic component. Nevertheless, the theoretical requirements of LS-DFMs about big enough cross section dimension of the panel data containing weak cross correlated idiosyncratic components are not necessarily satisfied in applications with real data. The results provided in this paper stress the need of deeper assessment of these methodologies in relation with the context in which they are implemented. None of the theoretical and computational limitations of the models seem to be determinant enough in order to completely discard any of the models in favor of the other in empirical applications. Thus, under the light of these findings, previous results in the literature, where DFM have been analyzed separately, should be prudently considered. Further research is needed in order to disentangle their causes, the effect of characteristics of the indicators included in the dataset, the ability of the models in correct estimation of the latent factors and the predictive power of the factors for a particular target variable.
Chapter 2

Great Recession and Monetary Policy Transmission

2.1 Introduction

In the last years, since the beginning of the Great Recession in 2008, the Federal Reserve has implemented a set of policy measures in order to stimulate the growth of the US economy. Official interest rates are currently at their lower bound and they will be eventually raised by policymakers. On the other hand, the twenty years previous to the collapse of the financial system were characterized by long expansions and the lowest volatility since the middle of the 20th century. After the magnitude and impact of the financial crisis in 2008, macroeconomic transmission mechanisms may have been affected. Therefore, policy decisions entail doubts about the size, effectiveness and duration of the consequences of ending the monetary stimulus. The response of real economy to raises in the official interest rates could be similar to the observed in the period previous to the Great Recession or, on the contrary, it may overreact after this stage of great volatility.

This paper tries to solve this issue identifying structural changes in the US economy
2.1. INTRODUCTION

during the Great Recession based on the dynamics of a large dataset of macroeconomics series during the last forty years. In order to exploit the information contained in the 110 monthly series included in the dataset, I combine several techniques to deal with the *dimensionality problems* inherent to a specification of this magnitude.

Conventionally, monetary policy analysis has been carried out by imposing plausible restrictions in Vector Autoregressive (VAR) innovations for the identification of the structural shock of interest. Thus, it is assumed that the innovations of the VAR span the space of the structural shocks. However, if there is a variable containing information related with the structural shock which is not included in the model its innovations will be biased due to the omission of this relevant variable. Given that the number of parameters estimated in a VAR increases as the square of the number of time series included in the model, this approach is not able to deal with large amounts of information and, consequently, the omission of relevant information becomes a plausible problem. In fact, this technical limitation has been argued as explanation for some of the results provided by the structural VAR literature which are not concealable with economic theory: raises of prices as consequence of a contractionary monetary shock, known as the Price Puzzle (Sims, 1992) and monetary policy changes which only affect exchanges rates with a considerable delay instead of contemporaneously, the Delayed Overshooting Puzzle (Eichenbaum and Evans, 1995).

More recently, factor decomposition has been included in the structural analysis literature in order to avoid the dimensionality problems of VARs in an attempt to reconcile theoretical predictions with empirical results. Under the assumption that the whole economy is driven by a reduced set of latent forces, large datasets can be summarized in a small number of factors which explain the most of the co-movement in the macroeconomic data. Due to its considerable smaller cross sectional dimension with respect to the observed data, factors can be included in economic analysis allowing for parsimonious specifications. The advantages of this approach at macroeconomic forecasting with respect to other models have been widely
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Bernanke, Boivin and Eliasz (2005) use this technique to combine a set of factors with federal funds rate in a VAR for the identification of monetary policy shocks. The inclusion of higher level of information in this model, known as Factor Augmented VAR (FAVAR), solves the Price Puzzle predicting reasonable responses in prices to monetary shocks. Moreover, this approach allows the estimation of the responses to monetary shocks in the large set of variables used for the estimation of the latent factors. Under their identification scheme, factors are computed as linear combination of "slow moving variables", those which are largely predetermined as of the current period assumed to be non-affected by federal funds rate contemporaneously. Therefore, the number of identification restrictions depends on the number of factors obtained from the data. Thus, a second dimensionality problem arises here. If the researcher choses a large number of underlying factors to closely mirror the observable dataset, the number of necessary restrictions will be larger as well. Given that the factors are statistical tools with no clear economic interpretation, it is difficult to find reasonable criteria to impose identification restrictions describing the relationship between federal funds rate and a relatively large set of estimated factors.

Gambetti and Forni (2010) overcome this limitation by using a Dynamic Factor Model (DFM) approach for structural analysis. These models are based on two sets of equations. A first group describing the contemporaneous relationship between observed data and the static factors, as those estimated in the FAVAR, and a second set of equations specifying the dynamic of the static factors with innovations driven by a smaller set of dynamic factors. In this setting, the number of static factors capturing the behavior of the observed data may grow without affects the amount of identification restrictions since they are imposed on the dynamic factors. Moreover, under the identification strategy of Gambetti and Forni (2010),

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2Bernanke, Boivin and Eliasz (2005) estimate 3 or 5 static factors from a dataset of 120 variables while Gambetti and Forni (2010) compute 16 static factors to summarize the behavior of a version of the same
restrictions are not imposed in the Impulse Response Functions (IRF) of the factors, which are posteriorly linked with the observable data. Instead, restrictions are directly applied into the IRF of the observed variables to the dynamic shocks. This allows us to estimate the factors for the whole dataset with no need of distinguish between slow and fast moving variables and, consequently, none of the available information is discarded. This framework provides reasonable IRF where not only Price Puzzle but also Delayed Overshooting Puzzle disappear.

Despite the advantages of the implementation of these dimension reduction techniques for structural analysis, previous literature assumes invariant relationship between monetary policy decisions and macroeconomic activity along time. However, this paper shows that this assumption becomes unrealistic for large periods of time and provides evidences of instability in a factor model applied to the US economy once data is updated including the Great Recession period.

Recent literature has devoted attention to this potential problem in DFMs. Banerjee, Marcellino, and Masten (2008) perform a Monte Carlo experiment to explore the consequences of changes in the model parameters on the forecast performance of the factors. They find that the effects of instability in the factors loadings fade away as long as temporal and cross sectional dimensions of the panel is large while, on the other hand, discrete changes in the law of motion of the factors may affect the forecast properties of the models. Stock and Watson (2009) study the effects of structural instability in the US between 1959 and 2006 using subsamples corresponding with Great Moderation period (McConnell and Perez Quiros, 2000). Their conclusions are consistent with those provided by Banerjee, Marcellino and Masten (2008): despite the presence of some instability in the factors loadings, most accurate results are based on factors estimated with the full sample in combination with forecast equations for each subsample. Given that the forecast equations implicitly contains the dynamic of the factors, they point out that the better results of this combination may
be due to the presence of instability in the parameters describing the law of motion of the factors although "additional analysis is required to confirm this conjecture".

This paper takes these findings as starting point and introduces this conjecture into a structural analysis context by assuming that i) the behavior of the whole economy can be explained as a stable function of unobservable forces, the factors, and ii) the interaction between those forces evolves differently over time. The study of this particular case of instability, within other considered in Stock and Watson (2009), presents two important advantages. First, it permits the existence of several breaks during large periods of time instead of just one. And second, it allows the identification of structural breaks in real time without using ex-post information to assume when these changes took place. This feature is included into the econometric framework using a model where the dynamic of the factors is governed by a Markov Switching (MS) process. Accordingly with this specification, and contrary to previous linear models, relations in the economy change as a function of a latent variable which captures regime shifts across time.

It is important to notice that the estimation of this model, where breaks in the dynamic of factors are allowed, is non-trivial and that a **third dimensionality issue** appears here. Given that observable data is summarized into several factors and that these factors follow different processes from one regime to another, the number of parameters to be estimated is considerably large and increases proportionally with the number of regimes. In order to deal with such a problem, I follow the estimation strategy proposed by Sims, Waggoner and Zha (2008) for large multiple equation MS models. Traditional maximum likelihood estimation procedures are not precise for sets of parameters too large with respect to the sample size. To overcome this limitation, they suggest a computationally tractable procedure based on Gibbs sampling where prior Bayesian information is included for the estimation of the posterior distribution of the parameters. Due to the complexity of large multivariate MS models, the posterior distribution may present non Gaussian shapes. For this reason, it becomes crucial to choose starting values for the Gibbs sampler close to the most likely scenario in order to
2.2. MODEL AND IDENTIFICATION

avoid series of posterior draws getting stuck in a low probability region. This is done by implementing a blockwise optimization algorithm for the selection of the starting values.

Results show the presence of two distinguishable structural scenarios and differences in the reactions of macroeconomic indicators to monetary policy shocks in each of these states. One state corresponds with periods of economic growth and low volatility and the other with periods of recessions and high volatility. State dependent responses are compared with those linearly estimated ignoring the presence of different structural scenarios before and after 2008. The inclusion of data corresponding to the Great Recession yields to important changes in the amplitude of these linear IRF for all the variables. The state dependent IRF belonging to the state characterized by low volatility and expansions are very similar to those computed linearly with data previous 2008. However, the shape and magnitude of the IRF linearly computed with the dataset until 2014 are clearly distorted by the form of the IRF for the state of high volatility and recessions. These facts stress the important effect of the data corresponding with the last years in the results and the necessity of an identification of separated monetary transmission mechanism under the presence of structural instability.

The rest of the paper is organized as follows. Next section describes the model. Section 3 contains the empirical analysis including data description, estimation process and results. Section 4 concludes.

2.2 Model and Identification

Consider $x_{it}$ as a macroeconomic series expressed on a monthly basis where $i = 1, \ldots, n$. These $n$ series composing the whole economy may be expressed as a function of a set of $r$ latent variable $f^1_t, \ldots, f^r_t$, the static factors, and an idiosyncratic component $\varepsilon_{it}$ only associated with $x_{it}$ or with a set of variables belonging to the same macroeconomic category:
2.2. MODEL AND IDENTIFICATION

\[ x_{it} = \lambda_1 f_{it}^1 + \ldots + \lambda_r f_{it}^r + \epsilon_{it} \] \hspace{1cm} (2.1)

Given that the static factors affects the \( n \) series, equation (1) is rewritten as

\[ X_t = \Lambda F_t + \xi_t \] \hspace{1cm} (2.2)

where \( X_t = (x_{1t}, \ldots, x_{nt})' \), \( F_t = (f_{1t}^1, \ldots, f_{rt}^r)' \), with \( 1 \leq r << n \), and \( \Lambda \) is a \( n \times r \) matrix.

The law of motion of the static factors, which are only contemporaneously related with the observable series, follows a different autoregressive process across time depending of the value of an unobservable Markov chain state variable \( s_t = 1, \ldots, h \). Thus,

\[ F_t = A_{1s_t} F_{t-1} + A_{2s_t} F_{t-2} + \ldots + A_{ps_t} F_{t-p} + \eta_t \] \hspace{1cm} (2.3)

Finally, the \( \eta_t \) innovations of equation (3) are driven by the set of \( q \) dynamics factors \( u_t \) loaded by the full rank \( r \times q \) matrix \( B_{st} \) which also depends on the state variable

\[ \eta_t = B_{st} u_t \] \hspace{1cm} (2.4)

The number of the static factors, \( r \), is bigger or equal than the number of dynamics factors, \( q \), because \( F_t \) consists of current and lagged values of the dynamic factors \( u_t \). This is known as the static representation of the DFM\(^3\).

\(^3\)See Bai and Ng (2007) for further description.
Thus, $x_{it}$ is a function of the dynamic factors and its corresponding idiosyncratic component:

$$x_{it} = \Lambda_i (I - A_{1s} L - A_{2s} L^2 - \ldots - A_{ps} L^p)^{-1} B_s u_t + \varepsilon_{it} \quad (2.5)$$

Notice that, accordingly with equation (5), any variable of interest to the researcher within the large set of available information for a particular economy, eventually depends on a reduced set of $q$ dynamic factors for a given state of the economy. Let us consider the dynamic factors as structural shocks and $\Lambda_i (I - A_{1s} L - A_{2s} L^2 - \ldots - A_{ps} L^p)^{-1} B_s$ as the IRF which measure the reaction of a given variable $x_{it}$ to a marginal change in $u_t$. Based on this representation of the dynamic of the economy, Gambetti and Forni (2010) define a useful strategy for the identification of the monetary shocks equivalent to those applied in structural VAR literature. Structural shocks in equation (5) are unidentified since they do not meet any requirement based economic theory. However, let us suppose that economic theory supports a set of restrictions in the contemporaneous or short term responses of a reduced set of variables to monetary structural shocks and that these timing restrictions can be summarized into an orthogonal matrix $H$. In that case, identified structural shocks are found by premultiplying $u_t$ by $H$ and its corresponding IRF are identified postmultiplying them by $H'$. If the number of variables supporting theory restrictions coincides with the number of dynamic factors, $H$ may be found under a standard triangularization scheme. As highlighted by Gambetti and Forni (2010), the number of identification restrictions can be larger than the number of dynamic shocks. However, this paper follows exactly their identification procedure to help comparison of the results.
2.3 Empirics

2.3.1 Data

Empirical applications of DFM for the U.S. economy are generally based on similar versions of the dataset used by Stock & Watson (1999). Remarkable examples are, Bernanke, Boivin and Eliasz (2005), Boivin and Ng (2006) or Stock & Watson (2012) among others. For the comparability of the findings with previous results, this dataset is also used here. To be precise, the dataset consists in 110 monthly US series which may be classified into the following categories: real output and income, employment and hours, housing starts and sales, inventories and orders, money and credit, interest rates, exchange rates, price indexes and stock prices. This panel exactly corresponds with the version of the Stock & Watson (1999) dataset used by Gambetti and Forni (2010). The sample starts in April of 1973 in order to avoid the fixed exchange rate and is updated to November of 2013 to include data corresponding with The Great Recession. Data transformation is carried out in line with previous FAVAR and structural DFM literature.

2.3.2 Estimation under Structural Instability

As mentioned in the previous section, static factors are not observable by the researcher. However, given that macroeconomic data are very collinear, Principal Component Analysis (PCA) may be applied for the estimation of a reduced set of latent series capturing the bulk of their co-movements. Let be $X$ the $t \times n$ matrix of data, static factors are computed by post multiplying $X$ by a $n \times r$ matrix $\Lambda$, containing in its columns the $r$ eigenvectors associated with the $r$ biggest eigenvalues of variance covariance matrix of $X$. This gives us a summary of the original data in terms of the amount of eigenvectors chosen by the researcher.

\footnote{The Index of Help-Wanted Advertising in Newspaper and its ratio with respect to employment were skipped because more recently they provide poor information about labor market conditions.}
2.3. EMPIRICS

Obviously, the bigger the number of eigenvectors the lower the loss of information caused by this reduction dimension technique. I apply the criteria proposed by Bai and Ng (2002) for the selection of the optimal number of static factors, $r$. These criteria, generally used in the factors model literature, are also implemented in Gambetti and Forni (2010). In particular, they chose $IC_{p2}$ criterion within the group of specifications proposed by Bai and Ng (2002) which points out 16 as the optimal amount of factors. Nevertheless, once their sample set is updated including data corresponding with the Great Recession, all the six versions of $IC$ and $PC$ suggest a value of $r$ equal to 25.

Due to the properties PCA dimension reduction technique, the relation between the latent factors and the observed data is assumed to be linear and stable along the analyzed period. Accordingly with Banerjee, Marcellino, and Masten (2008) and Stock and Watson (2009), the static factors can be correctly estimated by PCA even under structural instability as long as the temporal and cross sectional dimensions of the panel are large. The results of Banerjee, Marcellino, and Masten (2008) are based on Monte Carlo simulations for datasets of 50 series and 150 observations which are considerably smaller than the dataset used here. Alternatively, Stock and Watson (2009) estimate a set of factors using a whole panel US data between 1959 and 2006 and compare them with two sets of factors based on data before and after 1984 in order to capture the structural changes which take place during the Great Moderation\(^5\). They find that full sample estimations of the factors span the space of the subsamples factors by comparing their correlations. Accordingly with their results, the number of factors summarizing the full sample containing structural shifts was larger than the amount of factors mirroring the co-movements in the subsamples with more stable patterns. This explains why the number of factors selected by Bai and Ng (2002) criteria applied to the dataset of Gambetti and Forni (2010) is bigger once the dataset contains the Great Recession.

Moreover, in order to identify the main sources of instability in the model, Stock and

Watson (2009) apply the Chow test to the regression of the observable variables on full sample estimated factors for the pre and post 1984 periods. The same test is applied to four periods ahead direct forecast equation where the parameters estimated also contains the dynamic of the factor\(^6\). Surprisingly, they find more evidences of instability in the forecast equation than in the factor loadings equations. Moreover, most accurate results are provided by full sample factors in combination with forecast parameter estimated from split samples. This suggests that the structural instability comes from the dynamic of the factors although, as they highlight, this hypothesis requires a further assessment.

This paper explores this scenario. In order to mirror structural breaks in the transition of the forces driven the economy, it is assumed that the dynamic of the factors follows a MS process. This specification presents two advantages with respect to the analysis of Stock and Watson (2009). First, accordingly with the MS specification, the dynamic of the factors depends on an unobservable state variable estimated following standard procedures described below. Thus, structural breaks may be identified based on the currently available data and no ex-post information is required. And second, instead of consider a single break, the state variable evolves along the temporal dimension of the dataset allowing for multiple breaks.

The vector containing the state dependent autoregressive parameters and error variance covariance matrices of equation (3), \( \theta \), is computed based on the PCA estimation of the static factors. Notice that, as previously mentioned, these parameters depend on a state variable, \( s_t \), which mirrors changes in the macroeconomics patterns along time. Due to the uncertainty about when these changes take place, \( s_t \) is estimated. For this purpose, it is assumed that \( s_t \) follows a first order Markov switching process characterized by the probabilities of transition from one regime to another represented by a \( h \times h \) \( Q \) matrix where \( h \) is the number of regimes that may be taken by \( s_t \). Given the big amount of parameters that characterize a multivariate MS model, MLE may produce unreliable results for a relatively small sample size. Instead, estimation is carried out following the procedure proposed by Sims, Waggoner

\(^6\)See stock and Watson (2009), page 5 for details.
and Zha (2008) for large multivariate MS models based on Bayesian methods. The joint posterior density of $\theta$, $S_T = (s_1, s_2, \ldots, s_T)$ and $Q$ is complicated and, even if it is known, its integration to obtain the marginal distribution of the parameters may be unfeasible. Alternatively, Gibbs sampler is used to calculate the moments of the marginal posterior distributions by sampling iteratively from the conditional posterior distributions:

\[
\begin{align*}
\text{i) } & \quad p(S_T \mid F_T, \theta, Q) \\
\text{ii) } & \quad p(Q \mid F_T, S_T, \theta) \\
\text{iii) } & \quad p(\theta \mid F_T, S_T, Q)
\end{align*}
\]

i) Under the assumption that $s_t$ follows a first order Markov chain process, it can be shown that:\footnote{See Kim and Nelson (1999b) equation 9.14 for details.}

\[
p(S_T \mid F_T, \theta, Q) = p(s_T \mid F_T, \theta, Q) \prod_{t=1}^{T-1} p(s_t \mid F_t, \theta, Q, s_{t+1}) \tag{2.6}
\]

where $S_T$ may be drawn recursively for $t = T - 1, T - 2, \ldots, 1$. Initially, for a given initial value of the other MS parameters, Hamilton’s filter is applied forward to estimate $p(s_T \mid F_T, \theta, Q)$. Then $p(s_t \mid F_t, \theta, Q, s_{t+1})$ is generated based on

\[
p(s_t \mid F_t, \theta, Q, s_{t+1}) = \frac{p(s_t, s_{t+1} \mid F_t, \theta, Q)}{p(s_{t+1} \mid F_t, \theta, Q)}
\]
\[ p(s_{t+1} \mid s_t, F_t, \theta, Q)p(s_t \mid F_t, \theta, Q) \]
\[ = q_{s_{t+1}, s_t} p(s_t \mid F_t, \theta, Q) \]
\[ = \frac{q_{s_{t+1}, s_t} p(s_t \mid F_t, \theta, Q)}{p(s_{t+1} \mid F_t, \theta, Q)} \quad (2.7) \]

where \( q_{s_{t+1}, s_t} \) is a transition probability in \( Q \) from \( s_t \) to \( s_{t+1} \).

\[ ii) \quad \text{Conditional on the others parameters, the transition probability matrix } Q \text{ is generated from a Dirichlet distribution } D(\alpha_{i,j}) \text{ where } 1 \leq i, j \leq h. \quad \alpha_{i,j}, \text{ the hyperparameters which specified the form of the prior distribution, are chosen in order to mirror the duration of the NBER recessions and expansions. Precisely, the expected probability of staying in the same state is} \]

\[ E q_{j,j} = \frac{\alpha_{j,j}}{\alpha_{j,j} + (h - 1)} \quad (2.8) \]

\( \alpha_{i,j} \) is set equal to 1 for every \( i \neq j \) and, for the two regimes specification, \( \alpha_{i,i} \) is assumed to be equal 58.3 and \( \alpha_{j,j} \) to 12.16. In this way, the believes about the duration of the regimes are reflecting the average duration in months of the NBER recessions and expansions between 1973.4 to 2013.11 respectively.

\[ iii) \quad \text{The state dependent autoregressive parameters and error covariances are drawn as in the standard Bayesian VAR literature. } A \text{ is generated from the multivariate normal posterior and } \sigma_{\eta} \text{ from an inverse-Wishart posterior for each regime. Priors are set as in the version of the Minnesota prior defined by Sims and Zha (1998).} \]

However, given the complexity of large multivariate MS models, the posterior distribution
2.3. **EMPIRICS**

can present complicate shape. In order to avoid sequences of posterior draws stuck in a low probability region, a correct selection of the starting values for the Gibbs sampler becomes crucial. For this purpose, the set of coefficients to be estimated is partitioned into several blocks containing intercepts, autoregressive parameters, error covariances and the transition matrix. Then, an optimization procedure is applied iteratively for each of these blocks while holding the others constant until likelihood convergence is achieved. This procedure has been shown to increase likelihood more efficiently than the application of a maximization routine to the total set of parameters.

Finally, inference about the MS parameters is carried out after 10,000 iterations of the posterior sampler started with the initial values provided by the blockwise algorithm. To guarantee convergence, the first 3,000 iterations were discarded.

Once the estimation of the parameters in equation (3) is performed, the $r \times q$ matrix loading the dynamic factors $B_{st}$ is computed by applying again the PCA dimension reduction technique to the regime-dependent covariance matrices of the errors.

The scheme developed by Gambetti and Forni (2010) is reproduced for structural identification. The identification restrictions are based on: industrial production, prices, interest rates and exchanges rates. The set of contemporaneous IRF corresponding with these variables in this order in equation (5) are restricted to be lower triangular by a Cholesky decomposition. Identification is carried out by post multiplying the complete set of IRF in (5) by the quotient of the Cholesky factor over the set of contemporaneous IRF of these four variables. In this way, it is assumed that production and prices do not respond to interest rate changes within the same month and that interest rates do not respond contemporaneously to exchange rates while the reaction to a monetary policy shock for the remaining of variables included in the dataset remains unrestricted. This identification scheme requires a number of dynamic factors equal to the number of variables considered for identification ($q = 4$). Results of next section are based on this specification in order to help its comparability with respect to the findings provided by Gambetti and Forni (2010).
2.3. EMPIRICS

2.3.3 Results

At first, I assess the necessity of distinguishing between macroeconomic reactions to monetary policy shock along time. For this purposes, linear IRF for some representative variables of the different categories of the dataset are computed for a rolling window period. In this exercise IRF to a 0.5% increase in federal funds rate are estimated based on a subsample starting in April 1973 and finishing in January 2005. Then, the next monthly observation is added to the subsample and IRF are computed again. This step is iterated until the last available observation corresponding with November 2013 is included. For the sake of space, the rolling window IRF for the variables used for identification, industrial production, prices, federal funds rate and exchange rates, are depicted in Figures 2.1 to 2.4 respectively. For these four variables, it can be seen how IRF are very similar from one month to the next until the moment in which data corresponding with the Great Recession is included. Starting from this period, IRF’s amplitude jumps. Thereafter, there is a second group of IRF with a relatively stable shape month by month until the end of the sample. This pattern is also present in all the other rolling window IRF not presented here.

These preliminary results show the existence of structural instability in the DFM and provide evidences of changes and different magnitudes in the macroeconomic transmission mechanism during the Great Recession. In consequence, I apply the MS specification to identify the periods when these structural breaks take place. Figure 2.5 presents the smoothed probabilities of a second state once the estimation procedure described in the previous section is applied. In order to characterize this state, the probabilities are presented together with the periods classified as recessions by the National Bureau of Economic Research (shaded areas) and business cycle volatility (dotted line) defined as in Blanchard and Simon (2001): the standard deviation of GDP growth over the last 20 quarters which is assumed

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8 Results are available upon request.
9 Results are based on a two state specification. The estimated probabilities for a third state in the dynamic of the factors were negligible.
2.3. EMPIRICS

to be constant along the three months of each quarter to match monthly data. The figure
shows how structural changes in the dynamic of the factors take place during recessions and
periods of high volatility (as the inter-recessions periods between 1973 and 1983 or after the
2007 recession) with the single exception of the early 1990s recession which occurs during a
low volatility period.

For illustrative purposes, state dependent IRF are presented with linear IRF computed
with data up to November 2007 and with a second set of linear IRF including the Great
Recession data. To save space, not all the 110 IRF are offered in this paper. Instead, a set of
variables considered as being representative of the broad categories included in the dataset
are depicted in figures 2.6 to 2.10. Several conclusions emerge from this comparison:

As previously observed in the rolling window exercise, the growth in the amplitude of
the linear IRF, once data posterior to 2007 is added, is a consistent pattern which affects all
the linear IRF for all the 110 variables in the dataset. These differences are not minor. The
increases in the maximum value in the linear IRF including updated data are around the
double of those computed with data previous to the last recession. Industrial Production
Index (Figure 2.6, first row, columns 1 and 2) is a clear example of this fact. The reduction
in this index estimated with updated data reaches 2.5% while this quantity was around 0.9%
with the pre-Great Recession sample. A second remarkable example can be found in the
reaction of people unemployed for more than 15 weeks after the contractionary policy shock.
Here, the maximum amount estimated in 2007 is of 150,000 and during the Great Recession
raises to more than 500,000 people (Figure 2.9, third row, columns 1 and 2).

Moreover, 75% of the pre-Great Recession linear IRF are similar in shape and amplitude
to those estimated for the first state. For instance, see Federal Funds Rate (Figure 2.6, third
row, columns 1 and 3) or Purchasing Manager Index (figure 2.10, second row, columns 1 and
3) where these two IRF are almost identical.

These facts stress the distortionary effect that the inclusion of the Great Recession data
2.4 CONCLUDING REMARKS

causes in the estimates with respect to those computed with the dataset used in Gambetti and Forni (2010) where the most of the sample corresponds with a stable period. The consequences of the inclusion of more observation corresponding with a high volatility period in the linear IRF may be clearly seen in the Producer Price Index and M1 (Figure 2.7, first and second rows) or in the Unemployment Rate (Figure 2.9, last row) where the shape of the linear IRF computed based in the whole sample is evidently conditioned by the IRF of the second state.

2.4 Concluding remarks

This paper shows the existence of changes in the macroeconomic transmission mechanisms during the Great Recession by analyzing the presence of structural instability in a Dynamic Factor Model. Based on previous Monte Carlo simulations and empirical results which support the correct estimation of the factors under instability in their loadings, I examine the presence of breaks in the transition of the factors using estimation procedure for large multivariate Markov Switching models. This specification provides evidences supporting the presence of two different dynamics on the underlying factors driving the US economy during the last forty years.

The reaction of macroeconomic variables to monetary policy changes is estimated, firstly, without take into consideration the presence of structural instability. These responses present heterogeneous results when are compared with those in which the Great Recession data is included. This fact stresses the existence of instability and introduces uncertainty about the selection of the correct sample to mirror the current economic conditions. The estimation process proposed here allows the identification of these structural breaks and the evaluation of the reaction of a large dataset of variables to monetary policy shocks in each of those different structural situations. The comparison of these responses with those ignoring the presence of instability highlights the important consequences of the inclusion of data pre-
2.4. CONCLUDING REMARKS

senting heterogeneous macroeconomics patterns in the magnitude of the estimated effects of monetary policy changes. The distinction and identification of these changes are crucial in order to avoid misleading predictions.

Finally, in the existing situation, with no conclusive signs of economic recovery and doubts about duration and impact of the structural effects of the Great Recession on the macroeconomic patterns, this paper provides an appealing framework in order to helps policy decision about the eventual effects of abandoning the zero lower bound of the official interest rates.
Chapter 3

Short term evaluation of monetary policy, a counterfactual analysis based on Dynamic Factor Models

3.1 Introduction

The financial crisis of 2008 was followed by a decline on real activity, employment and prices without precedents in the recent economic history which has been compared with the effects of the crack of 1929. In order to prevent the dramatic consequences of this financial shock into the economy, the Federal Reserve (Fed) implemented a package of unconventional monetary policies. Firstly, official interest rates, the traditional monetary policy instrument, were decreased until their Zero Lower Bound (ZLB). Once this conventional tool was exhausted, the Fed complemented this measure with other mechanisms in order to alleviate the liquidity shortage and to reinforce the economic growth. These extraordinary policies were the Quantitative Easing (QE) and the forward guidance. The latter lied in a more aggressive communication strategy from the central bank to press down the market expectation about
3.1. *INTRODUCTION*

the duration of the ZLB period. The former consisted in large scale purchases of assets with money created electronically by the monetary authority.

Thereafter, a vigorous debate emerged about the correct way and timing of going back to an orthodox monetary situation in the case of US and about the adequacy of the implementation of these exceptional stimuli in Europe.

It is important to notice that a monetary experiment of this magnitude has provoke an unprecedented increase of the monetary base and, consequently, it entails high uncertainty about its future consequences openings new challenges from the policy maker’s perspective. Central bankers must find the correct balance between the premature and delayed timing in the tightening of the monetary policy while preserving financial stability and minimizing markets disruptions. A too early removal of the stimuli may cause a higher than desired slowdown in the macroeconomic performance if growth is not solid enough. It also will suppose an increase in sovereign cost which may have dramatic consequences in the public accounting of some European countries. On the other hand, a delay in the removal of these unconventional measures would be translated into hypertrophied central banks’ balance sheets, excessive dependence of the financial markets of the liquidity flowing from the monetary authorities and into higher inflation. Traditionally, it has been precisely inflation the main indictor followed for the evaluation of the monetary policy results. However, its current steady evolution at low levels makes prices less informative than in the past and monetary decision has to be now evaluated together with other signs of the economic performance. This paper tries to solve this issue by proposing an easy to implement methodology for the short term evaluation of the monetary policy decisions and their consequences in the real economy.

Let us consider the particular case of the US. The QE started with monthly purchases of Treasury Bonds and Mortgage Securities by $85 billion. In 2013, given the improvement in some macroeconomic indicators and with a low inflation rate, the Fed decided to taper QE by $10 billion per month, to $75 billion. At the beginning 2014 the Fed further taper
3.1. INTRODUCTION

the program by another $10 billion per month to $65 billion. Finally, still with no signs of high inflation rate and even some brief stages of deflationary pressure, QE was entirely ended during the last quarter of 2014 while the Fed announced an expected increase in FFR finishing the ZLB period by the end of 2015.

The effectiveness of these decisions in the US (Gagnon et al., 2010. Altavilla and Giannone, 2014) and their spillover effects to other countries (Aizenman et al., 2014. Rai and Suchanek, 2014) have been widely evaluated in recent researches. Differently, this paper contributes to this literature by analyzing the adequacy of the evolution of the monetary policy from the central banker’s perspective helping to identify the most appropriate exit strategy from the non-standard monetary policies. I compare the consequences of the policy-maker’s decisions by proposing an easy to implement model which allow us to simulate the consequences of several monetary policy paths in the economy in order to figure out what will be its repercussion in real indicators helping in the selection of the most appropriate exit path regarding its timing and magnitude.

Dynamic Factor Models (DFM) are a suitable framework for this purpose. They have been shown as a powerful tool for the estimation of latent factors capturing the aggregate behavior of the economy contained in a set of observable macro variables from different categories (Stock and Watson, 1991). On the other hand, DFM are also useful for short term forecasting (Camacho and Perez-Quiros, 2010). Its main advantage with respect to other forecast models is that they include all the available information at a given date independently of the differences in the publication lags of the series included in the model. It is done modifying the model in order to deal with “ragged ends” containing missing values at the end of the sample period. This particular feature is exploited here in order to include in the information set publicly available the decisions made by central bankers about the future path of policy rate in order to evaluate the adequacy of this decision from a counterfactual perspective.

This strategy allows us to directly evaluate the consequences of a defined monetary policy
3.1. INTRODUCTION

plan at a given date. Differently, Impulse Response Functions (IRF), usually estimated in the Structural Vector Autoregressive approach for monetary policy analysis, isolate the effect of an unanticipated shock in the monetary policy variable on a set of others macro indicators according to some identification restrictions. The structural interpretation, under one of the possible sets of restrictions which are not free of debate, is based on the assumption that the identified monetary innovations are the same as the disturbance term in the description of a central bank policy rule (see Hamilton, 1994, p. 335). Furthermore, these shocks, which contain information about the dynamic effects of the monetary innovations that take place in a single period, may not be directly related with a sustained policy path in the long run.

On the other hand, IRF estimates are based on the correlation of the variables during the full sample period. This implies that the estimated reaction of the indicators to the monetary variable is considered as valid at any time in the analyzed period. However, recent literature has shown changes in the macroeconomic relationships during expansion and recessions (Auerbach and Gorodnichenko, 2012). In contrast, the projection of the variable’s dynamic provided by the simulation method proposed here takes as departure point the state of the economy estimated through the common latent factor at a given date. DFM measures the contribution of the income, activity and monetary indicators to the evolution of the state of the economy. The future progress of the factor is forecasted based on its estimated autoregressive dynamic together with the contribution of future path of the monetary policy decided by the central banker via the Kalman filter. This procedure allows us to find the effects of given policy path on the future state of the economy and to produce reasonable forecasts of the variables according with the predicted factor. This implies that the projections carried out for the same simulated path in a different date will be different according to the state of the economy at that date.

An important concern for this purpose is how the different components of recent monetary policy (official interest rate, money creation and forward guidance) may be jointly evaluated from a strictly quantitative perspective for its inclusion in the empirical analysis.
3.2. THE MODEL

Previous research focus on monetary policy has mostly relied in Federal Funds Rate (FFR) as inclusive description of the Fed’s intervention (Christiano, Eichenbaum and Evans, 1999, or Bernanke, Boivin and Eliasz, 2005, among others). However, since the end of 2008, the moment in which FFR reached the ZLB, this variable is no longer informative about the monetary stimuli. Similarly, monetary base and other indicators summarizing the amount of money present a similar lack of variability previous to the Great Recession. Finally, the quantitative assessment of forward guidance and Federal Open Market Committee (FOMC) public statements in the media implies obvious challenges.

This issue may be solved using the methodology proposed by Wu and Xia (2014). Official interest rate determines the shape of forward rates as a summary of markets´ expectations about future movements of interest rates. Market expectations are also conditioned by the duration of the ZLB and the magnitude of money flow issued by the central bank. Thus, once FFR losses its informational content at the ZLB, forward rates (or markets expectations about the future yields) evolves according to unconventional monetary policies as QE and forward guidance. Based on the information contained on the forward rates, Wu and Xia (2014) elaborate a Shadow Rate (SR) synthetizing monetary policy conditions as traditionally did FFR even during the ZLB period. Interestingly, they show how this Shadow Rate is related with macro variables in the same way than FFR did before the Great Recession.

3.2 The Model

The implemented model for the evaluation of monetary policy is based in the pioneer DFM of Stock and Watson (1991). Accordingly with their specification, the evolution of the economy is summarized in a single latent factor estimated from four series, considered of relevance because of its relationship with demand, supply, employment and income. As in Mariano and Murasawa (2003) and Camacho and Perez Quiros (2011), this initial set of indicators is
enlarged with GDP and other indicators related with monetary policy.

The main assumption of this methodology is that each of the $i$ indicators included in the model are commonly affected by a latent factor plus an idiosyncratic component which only affects each of the series accordingly with the following equation:

\[
x^i_t = \beta_i f_t + u^i_t \tag{3.1}
\]

Each of the components of the right hand side of equation (1) follows an autoregressive dynamic of order $p$ and $q$ respectively:

\[
f_t = a_1 f_{t-1} + ... + a_p f_{t-p} + \epsilon^{f}_t \tag{3.2}
\]

\[
u^1_t = b^1_1 u^1_{t-1} + ... + b^1_q u^1_{t-q} + \epsilon^{u^1}_t \tag{3.3}
\]

...\]

\[
u^n_t = b^n_1 u^n_{t-1} + ... + b^n_q u^n_{t-q} + \epsilon^{u^n}_t \tag{3.4}
\]

where $\epsilon^{f}_t$, $\epsilon^{u^1}_t$, ..., and $\epsilon^{u^n}_t \sim iN(0, \sigma^2_i)$.

Equations (1) to (4) may be summarized into the following state space representation:
Given this state space representation of the system, the latent factor and parameters can
be estimated by maximum likelihood using the Kalman Filter.

Finally, the estimation procedure may be modified in order to deal with missing values and "ragged ends" at the last part of the sample period. This is carried out by avoiding the part of the Kalman gain matrix which corresponds to these missing observations in the update equation of the Kalman Filter algorithm giving no weight to the missing values.

3.3 Monetary policy effects. Data, estimation and results

As mentioned in the previous sections, DFM are a useful tool for the inclusion of the latest available data regardless their publications lag. This particular feature becomes key at short term forecasting. DFM outperform other models based in balanced panel because they ignore part of the already available information and, consequently, their projections are based in a smaller information set. This crucial advantage can be applied from the central banker perspective. The information set of the policymaker is larger than the information observable for other agents. Central bankers decide the future path of monetary policy accordingly with their assessment of the economic conditions and targets. Secondly, central banks may decide what part of this plan is revealed to the public, to which extent and in what precise date.

Let us consider then that the monetary authority has fixed a specific target for the policy rate in the next future and the corresponding path to achieve this goal. This paper proposes a quantitative assessment of this decision by the counterfactual comparison of the estimated consequences of this initial path and final target with other alternatives. This can be easily done by including this decision and the alternatives in the information set included for the estimation of the DFM’s parameters and projections.

For illustrative purposes, let us assume that the Fed consider that the macroeconomic
situation in now completely recovered of the consequences of the financial crisis of 2008 and decides to end all the stimuli going back to a monetary policy stance similar to the one previous to the Great Recession period. In order to ensure financial stability and to minimize market disruptions this target would be achieved progressively during the next years. If this monetary policy path is included in the dataset of a DFM, projections based in this information set will be based in the previous dynamic of the economy and the decisions of the monetary authority. One may evaluate the consequences of this path by comparing this results with another set of predictions based on, for instance, a monetary path where the Fed stance remains unchanged keeping the stimulus during the next years. This analysis is useful for the assessment of the consequences in the variables included in the model and for identification of the optimal path.

Traditionally this assessment would be carried out using FFR as the indicator mirroring the extent and direction of the Fed’s intervention in the economy. However, as mentioned in the introduction, FFR does not contain full information about Fed program since the end of 2008 when reached the ZLB, monetary aggregates also suffer this lack of variation previous to the financial crisis and forward guidance can be difficultly included into the quantitative assessment proposed here.

However, forward rates contains, as a summary of market expectations, the information relating all these measures included in the monetary policy toolbox. Accordingly with Wu and Xia (2014), the informational content of forward rates of different maturities may be used for the estimation of a Shadow Rate (SR) using the extended Kalman filter in order to deal with the no linearity of the short term maturities close to ZLB period. As shown in Figure 3.1, this estimated policy rate is very close to the FFR above the ZLB and summarizes the effects of QE and forward guidance once FFR is near to zero. Moreover, Wu and Xia (2014) show how the SR relationship with a large set of 97 macro series is the same that the relationship of FFR before 2008.

SR is included in the original dataset of Stock and Watson (1991) for the estimation of
the latent factor representing the state of the economy. This original dataset is composed by Total Retail Trade, Industrial Production Index (IPI), Employees on Nonfarm Payrolls and Real Personal Income selected because of their relationship with demand, supply, employment and income respectively. As in Camacho and Perez Quiros (2011), these initial set of indicators is enlarged with GDP and monetary indicators. In this particular case, I use SR for the reasons explained above. Finally, Consumer Price Index (CPI) is also included for the evaluation of the effects of monetary policy on prices.

Data was downloaded from Federal Reserve Bank of Saint Louis online database (FRED) the 4th of March of 2015 spanning the period between 1960.Q1 to 2014.Q4. SR was downloaded from Federal Reserve Bank of Atlanta website. Before its inclusion in the model for the estimation of the common component series were transformed to induce stationarity and SR was included with two lags in order to introduce in the model a delay in the reaction of real activity to monetary stimuli.

The selection of the simulated monetary policy paths was carried out by selecting five plausible targets for the policy rate in the medium term which are represented in Figure 3.2. First target is based on the assumption that the economy is fully recovered of the Great Recession effects and that the Fed decides to establish monetary policy conditions similar to those previous to the financial crisis when official interest rate where around 5%. Taking also into consideration that the target has to be achieved progressively in order to smooth market disturbances, path 1 is defined by linear interpolation from the current value of SR until 5.25% during the next two years. This is the most aggressive contractionary path considered here although a tightening of similar magnitude in the monetary conditions has been previously observed during the seventies. The second path is defined in order to abandon the ZLB progressively during two years and recover a conventional situation in the monetary policy environment. Hence, the evolution of SR is defined by linear interpolation between the current value and zero. The path 3 represents and scenario of no further intervention where SR remains unchanged during the next two years assuming that tapering
is not still a good decision. Path number 4 is symmetric to the second path where SR decreases until 2.66%. Finally, path 5 is symmetric to path 1. In that case SR reaches -10.55%.

Evolution of the quarterly rate of growth of Total Retail Trade, GDP, Employees on Nonfarm Payrolls, IPI, Real Personal Income and CPI during the next six quarters are included in Figures 3.3 to 3.8. As first result, it is important to notice that, the estimated evolution for activity indicators and prices are consistent with the magnitude and directions of the different monetary policy path. Yellow lines, corresponding with path number 3, represent the predicted behavior of the economy under no intervention from the Fed in the current monetary environment in the next years. Estimated progress of these macro variables under a contractionary monetary policy, represented by paths 1 a 2, is depicted in red. As expected, the growth of activity and income indicators is slower if monetary conditions evolves abandoning the ZLB (path 2) and more sluggish when recovering the pre-Great Recession monetary stance (path 1).

Let us consider the particular case of Retail Trade (Figure 3.3) as an illustrative example, the quarterly rate of growth of this indicator would remain in values between 0.5 and 0.4 percent with no changes in the level of intervention of the Fed while this value would be lower than 0.3 after five quarters under the contractionary path 1, aimed to reach a monetary context similar to 2007. On the other hand, activity and income indicators show a more vigorous pace for the expansionary policy path represented by the green lines. If policy rate followed path 5 moving away from positive values with the same quickness than path 1 but in opposite direction, quarterly rate of growth of Retail Trade would be 0.15% higher with respect to the case in which there were no changes in the policy rate (path 3) and 0.32% higher with respect to the most contractionary route (path 1).

This pattern is present in all the variables included for the estimation of the latent factor. GDP, depicted in Figure 3.4, shows an increasing growth during the next quarters. However, the implementation of contractionary policies will slow down this progressive pace.
Comparing the extreme cases, the six periods ahead quarterly rate of growth of GDP will be 0.27% bigger under path 5 than under path 1.

Employees, IPI and Personal Income quarterly rates, Figures 3.5 to 3.7, show a similar predicted downward trend. These indicators will have a growth as vigorous as previously observed only under the most expansionary policy path number 5. The six periods ahead predicted rate under path 1 will be 0.55%, 0.12% and 0.22% smaller respectively for these three indicators.

Results describing the different CPI evolutions are also consistent with the monetary policy stance simulated in each path as can be seen in Figure 3.8. The more expansionary, or less contractionary, the monetary policy path, the higher the pace of quarterly rate of growth of CPI. However, the progress of prices for each monetary scenario is very similar describing a modest but increasing rate of growth. These results are according with Wu and Xia (2014) where it is shown how, during the period 2009-2014, monetary policy has reinforce real activity without the cost of higher inflation. The procedure proposed here for the estimation of monetary policy effects in combination with this result may be compared with the so called Price Puzzle common in Structural Vector Autoregression literature where contractionary policy shocks are related with higher inflation (Sims, 1992. Christiano, Eichenbaum and Evans, 1999). Under this framework this puzzle is not present because the effects of monetary policy are evaluated over the forecasted evolution of prices in a given period. As previously mentioned, changes from the current monetary situation to an expansionary policy will accelerate the evolution of prices while a contractionary policy path will slow inflation down.

\[ \text{1Within the set of indicators included for the estimation of the latent factor, CPI and IPI are also specifically analyzed in Wu and Xia (2014). Differences in the estimated future evolution of these indicator under expansionary and contractionary policies are similar in magnitude with their estimates about the size of the effects of the monetary stimuli carried out by the Fed between 2009 and 2014. See Wu and Xia (2014) p. 17.} \]
3.4 Summary and concluding remarks

The unconventional stimuli implemented after the Great Recession has led to monetary conditions with no precedents in the recent economic history. This context entails a new challenge in policy making about the correct strategy to recover the traditional role and level of intervention of the monetary authorities.

This paper proposes an easy to implement methodology which allows central banks and researchers interested on repercussion of the removal of unorthodox stimuli, to evaluate the consequences of a defined future path for monetary policy on key macroeconomic indicators.

This methodology is based on the advantages at forecasting of Dynamic Factor Models for the inclusion of information observable at different temporal horizons. The inclusion in this model of a predetermined monetary policy path to be evaluated by the researcher and its comparison with other alternatives provide estimates of the evolution of some key macro series given is recent dynamic and the contribution of monetary conditions to the macroeconomic achievement.

The findings presented here provide a measurement of the success of the monetary authorities’ intervention in real economic conditions and show how this intervention has small effect on prices after the financial crisis. The predicted future reactions of real indicators and prices to expansionary or contractionary policy paths are similar in magnitude to those computed in previous research about the consequences of the monetary stimulus applied between 2009 and 2014.

The application of this methodology to a Large Scale Dynamic Factor Model (Doz, Giannoni and Reichlin, 2011) in order to use large dataset of indicators for the estimation of the common factors will allow us to compute the consequences of the monetary policy exit strategy in deeper detail by its evaluation on hundreds of macro series. This extension is left to future research.


Gambetti L and Forni M. 2010. The dynamic effects of monetary policy: A structural
factor model approach Journal of Monetary Economics. 57: 203-216


# Tables and Figures

## Table 1: Dataset per country and category

<table>
<thead>
<tr>
<th>Country</th>
<th>Key</th>
<th>Activity</th>
<th>Trade</th>
<th>Finance</th>
<th>Employment</th>
<th>Prices</th>
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Table 2: Subset of indicators included in the SS-DFM

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<td>Industrial Activity Indicator (EMI)</td>
<td>Electric Consumption</td>
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<td>Brazil</td>
<td>IPI</td>
<td>Retail Trade</td>
<td>Employment</td>
<td>Money Supply (M1)</td>
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<td>Chile</td>
<td>IPI (Manufacturing)</td>
<td>Retail Trade Volume</td>
<td>Civilian Employment</td>
<td>Money Supply (M1)</td>
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<td>IPI (Manufacturing)</td>
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<td>Money Supply (M1)</td>
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<tr>
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<td>IPI</td>
<td>Retail Sales Index</td>
<td>Electric Consumption</td>
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<td>Peru</td>
<td>IPI (Manufacturing)</td>
<td>Retail Trade Volume</td>
<td>Trade Index</td>
<td>Exports</td>
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<table>
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<td>Retail Sales Index</td>
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<td>Peru</td>
<td>IPI (Manufacturing)</td>
<td>Retail Trade Volume</td>
<td>Trade Index</td>
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Table 3. Ratio of RMSE of SS and LS DFM over the RMSE of an AR model for nowcast and forecast during the three months of the quarter.

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<tr>
<th>Country</th>
<th>NOWCAST 1st Month</th>
<th>NOWCAST 2nd Month</th>
<th>NOWCAST 3rd Month</th>
<th>Average NOWCAST</th>
<th>FORECAST 1st Month</th>
<th>FORECAST 2nd Month</th>
<th>FORECAST 3rd Month</th>
<th>Average FORECAST</th>
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<td>0.69</td>
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<td>0.74</td>
<td>0.71</td>
<td>0.69</td>
<td>0.65</td>
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<td>0.71</td>
<td>0.68</td>
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<td>--</td>
<td>0.67</td>
<td>0.66</td>
<td>0.66</td>
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<td>0.85</td>
<td>0.96</td>
<td>1.43</td>
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<td>MEXICO</td>
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<td>0.30</td>
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<td>0.48</td>
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<td>1.99</td>
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Figure 1.1: Time scheme for Nowcast and Forecast 1

Figure 1.2: Time scheme for Nowcast and Forecast 2

Figure 1.3: Time scheme for Nowcast and Forecast 3
Figure 1.4: Quarterly rate of growth of Argentinean GDP (solid line), nowcasted and forecasted quarterly rate of growth of Argentinean GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.

Figure 1.5: Quarterly rate of growth of Brazilian GDP (solid line), nowcasted and forecasted quarterly rate of growth of Brazilian GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.

Figure 1.6: Quarterly rate of growth of Chilean GDP (solid line), nowcasted quarterly rate of growth of Chilean GDP for the first two months of each quarter and forecasted quarterly rate of growth of Chilean GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.
Figure 1.7: Quarterly rate of growth of Colombian GDP (solid line), nowcasted and forecasted quarterly rate of growth of Colombian GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.

Figure 1.8: Quarterly rate of growth of Mexican GDP (solid line), nowcasted and forecasted quarterly rate of growth of Mexican GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.

Figure 1.9: Quarterly rate of growth of Peruan GDP (solid line), nowcasted and forecasted quarterly rate of growth of Peruan GDP by Small Scale (dotted line) and Large Scale DFM (dashed line) for the three months of each quarter.
Figure 2.1: 50 months ahead Industrial Production Index rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

Figure 2.2: 50 months ahead Consumer Price Index rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

Figure 2.3: 50 months ahead Federal Funds Rates rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.

Figure 2.4: 50 months ahead Swiss/US real Exchange Rate rolling window Impulse Response Function from January 2005 to November 2013 for a 50 basis points contractionary monetary policy shock.
Figure 2.5. Line: State-2 Smoothed Probabilities. Shaded areas: NBER Recessions. Dotted line: Business Cycle Volatility.

Figure 2.6: Impulse Response Functions in percentage for identification variables. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.
Figure 2.7: Impulse Response Functions in percentage for Producer Price Index, Money Stock M1, Real Personal Consumption Expenditures and Consumer Credit Outstanding. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.
Figure 2.8. Impulse Response Functions for New Orders: durable goods(%) , Nonfarm Housing Starts (%) , NAPM Inventories (index), and Capacity Utilization- Manufacturing(%). First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.
### Figure 2.9: Impulse Response Functions in percentage for Average Weekly Hours Index: Total Private Industries (%), Average Weekly Hours: Manufacturing (hours per week), Unemployment by Duration (thousand people) and Unemployment Rate (%). First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.
Figure 2.10: Impulse Response Functions for S&P’s Common Stock Price Index (%) and Purchasing Managers Index. First column presents linearly IRF for data until November 2007. Second column are linear IRF for the whole sample. Columns three and four are state dependent IRF for the whole sample.
Figure 3.1: Dotted line: Xu and Xia (2014) Shadow Rate. Black line: effective Federal Funds Rate. Shaded area: Zero Lower Bound Period (Percentage).

Figure 3.2: Gray line: Xu and Xia (2014) Shadow Rate. Dark red line (path 1): linear increase to achieve values of the policy rate of the pre-Great Recession period in two years. Red line (path 2): linear increase to achieve positive values of the policy rate in two years. Yellow line (path 3): constant policy rate during the next two years. Green line (path 4): symmetric to path 2. Dark green line (path 5): symmetric to path 1. (Percentage).
Figure 3.3: Forecasted quarterly rate of growth of Total Retail Trade under different monetary policy paths, percentage. Dark red line: path 1. Red line: path 2. Yellow line: path 3. Green line: path 4. Dark green line: path 5.

Figure 3.4: Forecasted quarterly rate of growth of GDP under different monetary policy paths, percentage. Dark red line: path 1. Red line: path 2. Yellow line: path 3. Green line: path 4. Dark green line: path 5.
Figure 3.5: Forecasted quarterly rate of growth of Employees on Nonfarm Payrolls under different monetary policy paths, percentage. Dark red line: path 1. Red line: path 2. Yellow line: path 3. Green line: path 4. Dark green line: path 5.

Figure 3.6: Forecasted quarterly rate of growth of Industrial Production Index under different monetary policy paths, percentage. Dark red line: path 1. Red line: path 2. Yellow line: path 3. Green line: path 4. Dark green line: path 5.
Figure 3.7: Forecasted quarterly rate of growth of Real Personal Income under different monetary policy paths, percentage. Dark red line: path 1. Red line: path 2. Yellow line: path 3. Green line: path 4. Dark green line: path 5.
