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UNIVERSIDADE D
COIMBRA

Joshua Dias Duarte

Financial Development and consumption

Tese no âmbito do doutoramento em Economia orientada pelo Professor Doutor Pedro Miguel Avelino Bação e pelo Professor Doutor João Alberto Sousa Andrade e apresentada à Faculdade de Economia da Universidade de Coimbra.

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Orientadores:
Professor Doutor Pedro Miguel Avelino Bação
e
Professor Doutor João Alberto Sousa Andrade

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Resumo

Nesta dissertação estudamos o impacto do desenvolvimento do sistema financeiro sobre o consumo através de uma abordagem empírica. Para tal usamos quatro metodologias, as quais salientam aspectos diferentes do comportamento do consumo e formas diferentes de incorporar o efeito do desenvolvimento do sistema financeiro.

Começamos por estimar um modelo *Panel Vector Autoregression* (PVAR) para estudar a relação entre uma nova medida lata do desenvolvimento financeiro e um conjunto de variáveis macroeconómicas cruciais, entre as quais se inclui o consumo. Os resultados das estimações sugerem que o desenvolvimento do sistema financeiro tem um impacto positivo sobre o produto interno bruto (PIB) e sobre o investimento, mas que o efeito sobre o consumo é menos notório. Estes resultados sobrevivem a uma bateria de testes de robustez e são mais fortes numa subamostra de países com níveis de desenvolvimento financeiro mais elevados.

No segundo capítulo empírico, usamos o procedimento de *Panel Smooth Transition Regression* (PSTR) para estimar um modelo *Panel Error Correction Model* (ECM) para o consumo, de forma a averiguar como varia a relação entre o consumo e os seus determinantes quando o nível de desenvolvimento financeiro toma valores diferentes. Os resultados indicam que o aumento do nível de desenvolvimento financeiro reduz a reacção do consumo aos seus determinantes no curto prazo, mas também conduz a um ajustamento mais rápido em direcção ao equilíbrio de longo prazo.

No terceiro capítulo empírico, aplicamos as metodologias de *Panel Threshold Regression* (PTR) e *First Difference Generalized Method of Moments* (FD-GMM) para estimar com modelo com efeito *threshold*. A diferença reside na hipótese de exogeneidade das variáveis explicativas: o procedimento PTR supõe exogeneidade e o procedimento FD-GMM não. Estimamos o modelo para o consumo tendo como variáveis explicativas o rendimento, a riqueza e a taxa de juro, e considerando como medidas do nível de desenvolvimento financeiro ou uma medida lata do desenvolvimento do sistema financeiro ou o crédito. Em ambos os casos encontramos indícios da existência de um efeito *threshold* do nível de desenvolvimento financeiro sobre a forma como o consumo responde às outras variáveis do modelo.

Finalmente, usamos métodos de regressão não paramétricos no quarto capítulo empírico. O modelo, que inclui o consumo desfasado, o rendimento, a riqueza, a taxa de juro e o nível de desenvolvimento financeiro, procura descrever de forma mais geral o tipo de ligação que se pode encontrar entre o consumo e o nível de desenvolvimento financeiro, bem como ser informativo quanto à forma funcional da relação entre o consumo e os seus determinantes típicos. Os nossos resultados apontam no sentido de as ligações entre o consumo e os seus determinantes serem claramente não lineares. Quanto ao nível de desenvolvimento financeiro, concluímos que o seu efeito sobre o consumo depende fortemente do valor das restantes variáveis.

Classificação JEL: E20, E21, E44, G20.

Palavras-chave: Desenvolvimento Financeiro, Consumo, Panel VAR, Panel Smooth Transition Regression, Error Correction Model, Panel Threshold Regression, First Difference Generalized Method of Moments, Regressão não paramétrica, Local Linear Least Squares

Abstract

In this dissertation we take an empirical approach to the study of the impact of financial development on consumption. We use four different methodologies, which stress different aspects of consumption behavior and different ways of considering financial development's effect.

We start by estimating a Panel Vector Autoregression (PVAR) model to study the relation between a new broad measure of financial development and a set of core macroeconomic variables which includes consumption. The results from these estimations suggest that while financial development has a positive impact on Gross Domestic Product (GDP) and on investment, the evidence of an impact of financial development on consumption is weaker. These results survive a battery of robustness checks and are stronger in a subsample of countries with higher levels of financial development.

In the second empirical chapter, using the Panel Smooth Transition Regression (PSTR) method, a Panel Error Correction Model (ECM) is estimated for consumption, in order to study how the relation between consumption and its determinants changes for different values of financial development. The results suggest that higher financial development leads to a smaller reaction of consumption to its determinants in the short run, but also to a faster adjustment towards the long run equilibrium.

In the third empirical chapter, we apply Panel Threshold Regression (PTR) techniques and a First Difference Generalized Method of Moments (FD-GMM) methodology to estimate the threshold model. The difference is in the assumption of exogeneity of the explanatory variables. PTR assumes exogeneity while FD-GMM does not. We regress consumption on income, wealth and the interest rate and consider as measures of financial development both a broad measure of financial system development and a measure of credit. In both cases we find evidence of a threshold in the financial sector variable which affects how consumption responds to the other variables in the model.

Finally, we use nonparametric regression methods in our fourth empirical chapter. The model, which includes lagged consumption, income, wealth, the interest rate and financial development, aims at describing in a more general way the kind of link one can find between consumption and financial development, as well as providing some evidence of the shape of the relationship between consumption and its typical explanatory variables. Our results point towards distinctly nonlinear links between consumption and the regressors. As for financial development, we find that its effect over consumption is highly dependent on the value of the remaining regressors.

JEL Classification: E20, E21, E44, G20.

Keywords: Financial development, Consumption, Panel VAR, Panel Smooth Transition Regression, Error Correction Model, Panel Threshold Regression, First Difference Generalized Method of Moments, Nonparametric Regression, Local Linear Least Squares.

Abreviations

AIC - Akaike Information Criterion

BIC - Bayesian Information Criterion

BIS - Bank for International Settlements

DTF - Distance to Frontier

ECM - Error Correction Model

FD-GMM - First Difference Generalized Method of Moments

FRED - Federal Reserve Economic Data

GDP - Gross Domestic Product

GMM - Generalized Method of Moments

GVAR - Global Vector Autoregression

IMF - International Monetary Fund

IRF - Impulse Response Function

IV - Instrumental Variable

LM - Lagrange Multiplier

LLLS - Local Linear Least Squares

NLS - Nonlinear Least Squares

OECD - Organisation for Economic Co-operation and Development

OLS - Ordinary Least Squares

PSTR - Panel Smooth Transition Regression

PTR - Panel Threshold Regression

PVAR - Panel Vector Autoregression

RE-PIH - Rational Expectations Life Cycle Theory/Permanent Income Hypothesis

SE - Standard Errors

TV-PSTR - Time Varying Panel Smooth Transition Regression

US - United States of America

USD - United States Dollar

WTI - West Texas Intermediate

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Chapter 1

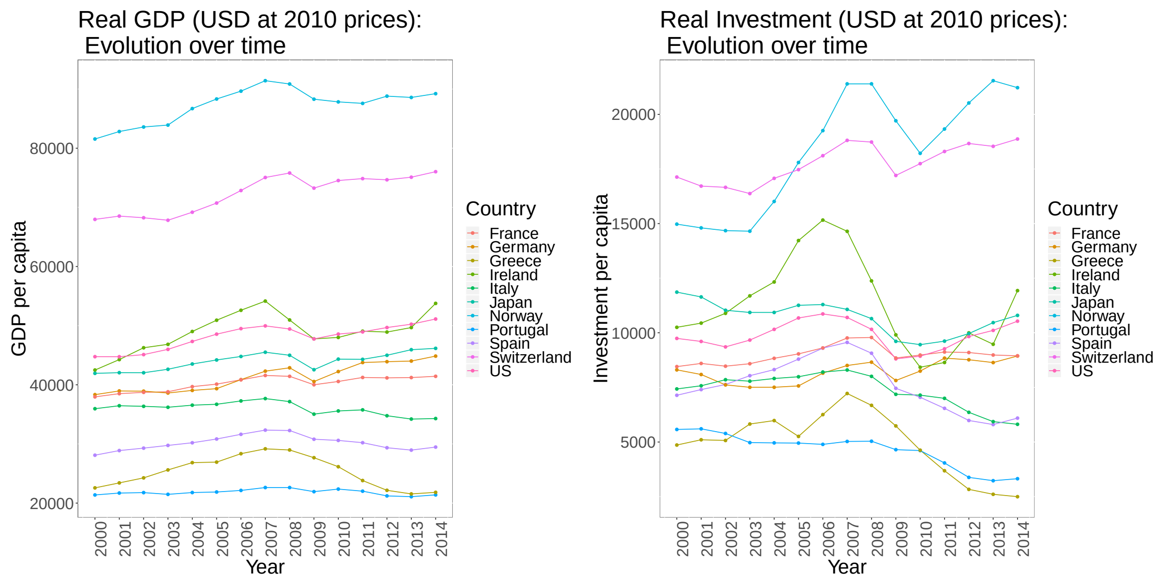
Introduction

This dissertation focuses on the question of whether one can find evidence of a connection between financial system development and aggregate consumption. While it can be said "the basic functions of a financial system are essentially the same in all economies — past and present [...] the functions of the financial system are far more stable than the identity and structure of the institutions performing them" (Merton, 1992, p.13), in the light of the recent events related to the international financial crisis, a reflection on the role of finance is modern economies is unavoidable. Namely, one should consider how changes in the financial system affect the rest of the economy (Stiglitz, 2010; Greenspan, 2010; Hall, 2011; Fornari and Stracca, 2012; Angelopoulou et al., 2014). This possibility that finance matters is obviously not new. For instance, Bernanke (1983) discussed it in the context of the Great Depression.

The main macroeconomic variables were strongly hit by the crisis. In fact, for some of them it is not clear that they have recovered to the level they would have had in the absence of the crisis. Figure 1.1 shows the evolution of investment and Gross Domestic Product (GDP) from 2000 to 2014 in a sample of developed countries. The impact of the crisis is clear in 2007-2009, but especially in the year 2009. The impact on consumption—see fig. 1.2—was not as clear-cut. In some countries there barely appears to be any evidence of an impact of the crisis on consumption. On the other hand, in the countries that were the most affected by the crisis, such as Ireland and Greece, the drop in their consumption levels is striking. Finance was at the center of the international financial crisis, sometimes called the "subprime crisis". What we are interested in studying in this dissertation is whether the differences across countries in the behavior of consumption during this period can be related to differences in the level of financial development.

However, before one proceeds to study that relation one needs to have a measure of financial development. In fig. 1.3 we plot the evolution of the commonly used indicators of the level of financial development. With the exception of the broad financial development index, those indicators focus on specific aspects of the financial system, such as credit or the stock market.

Figure 1.1: GDP and investment over time and space

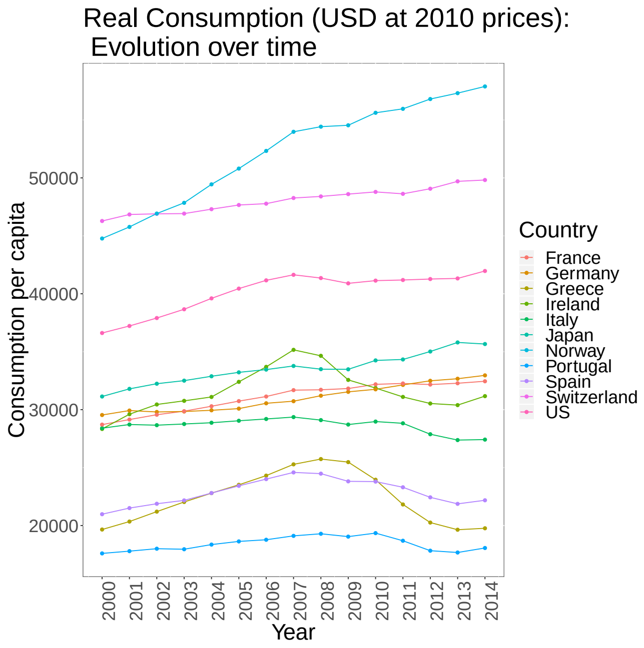


Source: See appendix A.1.

However, we should go back one step and begin by considering what the financial system is about. Merton (1992) defines the financial system as the facilitator of the allocation and deployment of economic resources in an uncertain economy. Another brief definition of the financial sector can be found in Alexander et al. (2000): “The financial sector is the set of institutions, instruments, and the regulatory framework that permit transactions to be made by incurring and settling debts; that is, by extending credit. The financial system makes possible the separation of the ownership of wealth from the control of physical capital” (p.12). The definition given in World Bank (2017) is that the financial system includes “a country’s financial institutions (banks, insurance companies, and other nonbank financial institutions) and financial markets (such as those in stocks, bonds, and financial derivatives). Also includes the financial infrastructure (for example, credit information-sharing systems and payments and settlement systems)” (p.xviii). The functions of the financial system have been listed in Cihak et al., 2013 as “(1) producing and processing information about possible investments and allocating capital based on these assessments; (2) monitoring individuals and firms and exerting corporate governance after allocating capital; (3) facilitating the trading, diversification, and management of risk; (4) mobilizing and pooling savings; and (5) easing the exchange of goods, services, and financial instruments” (p.5).

As we can see from the previous definitions and functions of the financial system, the financial system is a multidimensional concept. That makes it more difficult to define in a clear and precise way what financial development is. For instance, two working definitions of

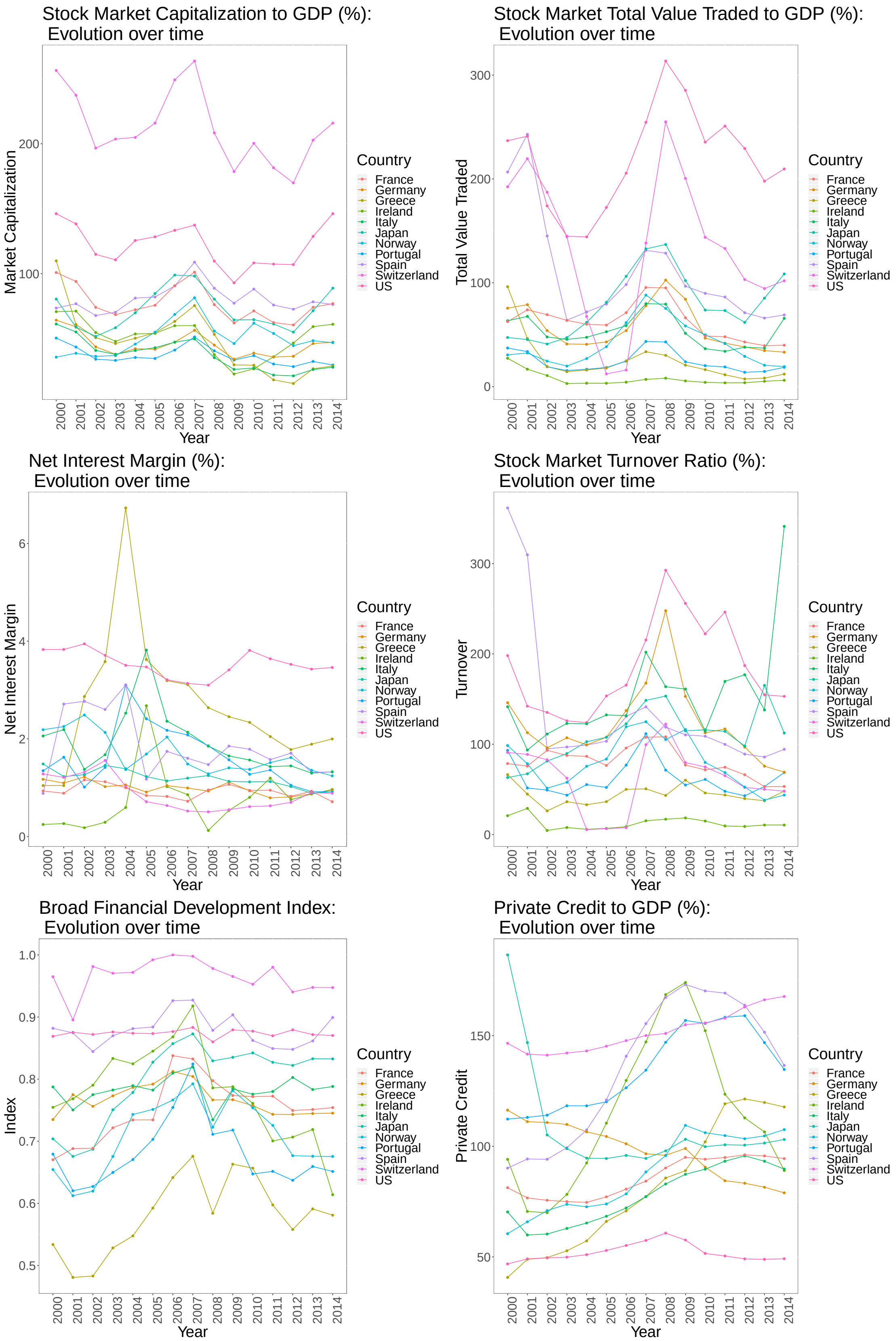
Figure 1.2: Consumption over time and space



Source: See appendix A.1.

financial development are "conceptually, a process of reducing the costs of acquiring information, enforcing contracts, and making transactions" (World Bank, 2017, p.xviii) and "the ability of the financial system to research firms and identify profitable ventures, exert corporate control, manage risk, mobilize savings, and ease transactions" (Levine, 1999, p.11). Several measures of financial development have been used in the literature—see, for example, the measures described in Valickova et al. (2015). Many of those measures focus on very specific aspects of financial system development. Nevertheless, efforts have been made to build extensive databases with measures of possible components of financial development, one leading example being the database described in Beck et al. (2010). The effect that the financial system can have over the rest of the economy is intimately related to how well it is capable of performing each of its functions. Yet, while the financial system is performing each of those functions it may be exerting different effects on the economy. This possibility is envisaged by authors who find that different combinations of financial services are optimal at different stages of the financial development process (e.g., Demirgüç-Kunt et al., 2013). Nonetheless, the various components of the financial system are interconnected and, as such, a general measure of financial development (which should also take into account the relative importance of each part of the financial sector) can be useful when studying the effects of financial development on macroeconomic aggregates. This kind of aggregate measure of financial sector development is what Svirydzenka (2016) strives to develop, providing a broad overview of the level of development of a country's financial system.

Figure 1.3: Financial development indicators over time and space



Source: See appendix A.1.

As for consumption, it is useful to recall some of the conclusions from theoretical models of consumption behavior. The main theoretical pillars for studying consumption behavior are provided by the Rational Expectations Life Cycle Theory/Permanent Income Hypothesis (RE-PIH) which started with the seminal works of Modigliani and Brumberg (1954) and Friedman (1957).

The paper by Modigliani and Brumberg (1954) was first presented as a way of trying to link economic theory with empirical evidence on consumers' behavior. Through a set of assumptions on the utility function's behavior, Modigliani and Brumberg (1954) are able to replicate empirical facts with their theoretical model of consumption. The main argument Modigliani and Brumberg (1954) make is that the proportion of income which goes to saving is independent of income levels. They base this argument on the proposition that saving is a mechanism used to face both specific major income variations, such as retirement, that occur during a household's life cycle as well as unforeseen emergencies.

The central idea that comes from the Life Cycle Theory, and which is also adopted by the Permanent Income Hypothesis, is that consumers engage in long-term planning when deciding how much they will be consuming at different moments of their life cycle. Friedman (1957) embraces this idea with the distinction between permanent and transitory components of income and consumption. The permanent component of income reflects factors related to the individuals' lifetime wealth, while the transitory component contains all the other factors, most of them relating to unexpected circumstances. Similar notions are applied to the distinction between the transitory and the permanent components of consumption. The main point of the permanent income hypothesis presented in Friedman (1957) is that permanent consumption is related to permanent income, with the ratio between the two of them determined by a certain set of variables, such as the interest rate or the ratio of nonhuman wealth to income. Additionally, the transitory components of consumption and income are not correlated with each other. The existence of permanent and transitory components in a variable can be accounted for by the usage of forecasting techniques based on exponential averaging, as shown by Muth (1960). Under certain conditions, permanent income can be optimally estimated to be an exponentially weighted average of past observed incomes. An extension of the life cycle theory to the aggregate consumption case is considered by Ando and Modigliani (1963). Ando and Modigliani (1963) use assumptions very similar to those in the original life cycle models. They arrive at a specification including nonproperty income and net worth. Ando and Modigliani (1963) remark that their consumption function is very close to the typical Keynesian one.

Under stronger assumptions, one can derive testable implications from the life cycle/permanent income hypothesis. Hall (1978) is a prominent example of this. The central implication derived and tested by Hall (1978) is that once lagged consumption is accounted for, no other lagged variable should have explanatory power for period consumption. It is important to mention that this relies on the absence of liquidity constraints. Empirical evidence contradicting that implication of the theory has been widely reported in the literature—see, e.g., Grossman and Shiller (1981), Daly and Hadjimatheou (1981), and Mankiw (1981). This particular aspect of the theory would later give rise to the excess sensitivity branch of the consumption literature, with one of the first papers in this specific topic being Flavin (1981) which introduces a test for the concept of excess sensitivity of consumption to income while trying to address the conflicting results of Hall (1978) and Sargent (1978).

From the excess sensitivity results stemmed what the literature has come to know as the Campbell-Mankiw framework, embodied in Campbell and Mankiw (1989, 1990, 1991). This framework considers the population as being composed of two types of consumers: those who behave as the permanent income hypothesis indicates and those whose consumption closely tracks current income. The share of consumers following the latter kind of behavior is related to the excess sensitivity of consumption to current income.

Within the many explanations that have been suggested for the excess sensitivity phenomenon (for instance, habit formation—see Sommer, 2007), one that stands out and has become a staple over the years is that of liquidity constraints, as suggested for example in Jappelli and Pagano (1989). This explanation for the excess sensitivity comes from the typical assumptions underlying the RE-PIH. These include a complete and perfectly working financial system, even if not explicitly stated, so that the consumer can freely transfer resources across time, enabling the consumer to implement the optimal plan for lifetime consumption. The existence of liquidity constraints compromises this and forces some agents to constrain their consumption by their current income. This in turn can cause the excess sensitivity observed in the data. Examples of how liquidity constraints might impair optimal consumption behavior can be found in Jappelli and Pagano (1994) and in Engelhardt (1996).

Closely related to the excess sensitivity and the liquidity constraints literature is the line of work that focuses on how credit affects consumption behavior. Credit is one of the main driving forces behind the intertemporal resource allocation mechanism that makes intertemporal consumption smoothing possible. This means that, at least to some extent, it is plausible to view credit as having some effect over aggregate consumption behavior—see, e.g., Muellbauer and Murata (2009), Muellbauer and Williams (2012) and Aron et al. (2012).

Much of the research done on the impact of financial sector development on consumption came after the deregulation processes that occurred in several major economies. Despite the fact that—as we can conclude from the brief description of consumption theory above—financial sector development has been given very little importance in the study of consumption behavior, there is clearly space for arguing that financial development may have an effect on consumption. The typical consumption theory leans heavily towards intertemporal choice theory. The assumption of perfect financial markets is a very important one in that context, but it is also a strong assumption to make. In reality, financial markets are not perfect and the financial sector has been constantly evolving. This means that the way in which a consumer can optimize the allocation of lifetime resources has been changing and it is possibly not the one implicit in theoretical models of consumption. The literature on the effect of financial sector development on consumption has mostly focused on the previous argument and applied it to the case of liquidity constraints—see, for example, Blundell-Wignall et al. (1991) ,Girardin et al. (2000), and Fernandez-Corugedo and Price (2002). This literature finds evidence that as the level of financial development, in a broad sense, increases, liquidity constraints tend to go down. With the recent financial crisis, the topic of financial innovation and development gained relevance once more. The subsequent literature on the effects of financial development on consumption took a different approach to the matter, turning its attention to how changes in the financial sector induced changes in the way consumption reacts to other variables, as in Fisher et al. (2012), Lee (2013) and Aron and Muellbauer (2013).

From the exposition above, we conclude that the theory of consumption behavior has evolved over the years and given itself room to accommodate several modifications, in order to better explain new regularities observed in the real world. Financial sector development has the potential to become one of these new relevant aspects that should be considered when thinking about aggregate consumption. The literature has advanced towards this, but progress is made harder by the fact that financial development is a multidimensional concept and by the fact that it is not clear how an empirical model of consumption should account for the impact of financial development. In this dissertation we attempt to make progress on this issue. In essence, this dissertation is a compilation of four papers that try to provide empirical evidence concerning the relationship between financial development and aggregate consumption. Each of the papers/chapters addresses the topic using a different approach to the empirical modeling of consumption and its relation with financial development.

First, in chapter 2, we analyze how consumption and financial development behave in a general framework given by a Panel Vector Autoregression (PVAR). This model includes other macroeconomic variables besides consumption and financial development, namely GDP, investment, the monetary aggregate, the exchange rate, interest rate and prices. It provides a way to assess the role of financial development in the context of general, linear macroeconomic relations. We use a panel dataset of yearly observations from 1981 to 2013 for 36 countries.

The results provide some evidence that financial development, in a broad sense, might be related to consumption, but the linear model does not appear adequate for the study of that relation. Therefore, we try to find evidence of a nonlinear relation. To this end, we choose two specifications of consumption behavior and introduce nonlinear elements in them. The nonlinear elements are either a regime change threshold or a smooth transition between regimes. The application of nonlinear estimation techniques gives us a different view of the relation between financial development and consumption.

Chapter 3 is the first of the two chapters that focus on this approach. There we apply the Panel Smooth Transition Regression (PSTR) methodology of González et al. (2017) to a Error Correction Model (ECM) specification for consumption behavior, in a panel dataset of 46 countries with yearly observations from 2000 to 2014. The models allow for both a direct and an indirect effect of financial development on consumption behavior. This indirect effect works through the responses of consumption to the other variables. The results provide evidence of the existence of such an effect in our data.

This line of analysis is continued in chapter 4. In that chapter we employ a model for consumption growth with the standard regressors plus financial development. The nonlinear component now takes the form of a threshold function that induces a discrete change in the coefficients of the model, i.e., a regime change. As in the previous chapter, the nonlinearity is ruled by the level of financial development. We estimate the model using two procedures. The fist is the Panel Threshold Regression (PTR) of Hansen (1999), which does not allow for possible endogeneity problems. The second estimator is the First Difference Generalized Method of Moments (FD-GMM) and Seo and Shin (2016). Again the results suggest that the indirect effect mentioned above exists. There also appears to exist a direct, nonlinear effect of financial development on consumption.

Our final approach employs a model general framework for analyzing nonlinearities in consumption behavior, namely those related to the level of financial development. To this end we model consumption as a function of financial development and standard explanatory variables in consumption models, in a completely nonparametric setting. This allows us to analyze the relation between financial development and consumption without any a priori assumptions on its functional form, beyond that incorporated in the choice of the explanatory variables. Thus, in chapter 5 we estimate a nonparametric model of consumption with the Local Linear Least Squares (LLLS) methodology of Stone (1977) and Cleveland (1979). Again, the results suggest that financial development affects consumption behavior in a nonlinear way. The nonlinearity appears to be related to the level of economic development. Additionally, consumption also appears to be nonlinearly related to the other explanatory variables.

Chapter 6 provides a brief review of the results reached in this dissertation and offers ending remarks on them.

We close this introductory chapter with a brief note on the way we apply the estimation and testing techniques. The methodologies we use throughout the dissertation are applied using the econometric software R (R Core Team, 2018) and Stata (StataCorp, 2017). Specifically, for Stata we use the commands *xtreg*, *xthreg* (Wang, 2015), *xthenreg* (Seo et al., 2019), *xtcointtest* and *pvar* (Abrigo and Love, 2016). For R we use the packages *plm* (Croissant and Millo, 2008; Millo, 2017; Croissant and Millo, 2019), *PSTR* and *np* (Hayfield and Racine, 2008).

Chapter 2

Financial Development and Economic Activity: A PVAR model

2.1 Introduction

The international financial crisis of 2007-2008 has had a two-fold effect on the way we see the financial system. First, it has highlighted the importance of the financial system for macroeconomic fluctuations (e.g. Brunnermeier et al., 2013). Second it has reinforced the skepticism regarding the effects of financial development on macroeconomic performance (e.g. Greenspan, 2010, and Stiglitz, 2010). Consequently, there has been a renewed interest on the macroeconomic implications of development in the financial sector and a reevaluation of the role that the literature (e.g. Merton, 1992) assigns to the financial system.

Financial development is a multidimensional process that occurs in the financial system, but may affect the rest of the economy. It encompasses developments in both financial institutions and financial markets, shaping the way in which the financial system will fulfill its primary role as an allocator of resources in an environment characterized by uncertainty (Merton, 1992), and all the functions which come with that role (Cihak et al., 2013). The wide range of functions which the financial system performs implies that it has ramifications over important aspects of the economy. Consequently, financial development should have a widespread impact as well, despite the fact that specific markets and institutions may have narrow roles and therefore narrow impacts (Gambacorta et al., 2014). This calls for the use of a measure of financial development capable of capturing the multiple facets of the process of financial development and of its influence on macroeconomic variables.

Our aim in this chapter is to assess the overall effect of financial development over a group of key macroeconomic variables. For that we use a PVAR model, estimated on a panel dataset with yearly observations from 1981 to 2013 for 36 countries. The PVAR model includes a wide set of variables which capture various aspects of an economy, from the monetary sector to macroeconomic aggregates, together with a broad measure of financial development.

Our results point toward a positive effect of financial development on GDP and investment, a result which is in line with the finance-growth nexus segment of the literature. We also find some evidence of a possible impact on consumption. Our results are robust to different variable orderings and PVAR orders, as well as to controls for the crisis period. Additionally, when we divide our sample into high financial development countries and low financial development countries, we find evidence of a nonlinearity in the impact of financial development. Namely, we find that the positive effects of financial development on the macroeconomic aggregates only show up for the high level group.

Our contribution to the literature on the impact of financial development on the economy derives from the use of a recent estimation technique on a new panel dataset. The measure of financial development that we use is, to the best of our knowledge, the broadest one available. We also compare the results obtained with this new measure with the results provided by the use of more traditional measures of financial development. This allows us not only to obtain an estimate that may be closer to the overall impact of financial development on an economy, but also to analyze the different aspects of financial development which are highlighted by alternative measures. In addition, our battery of robustness checks provides increased confidence in the results reported here. The results reported here confirm several conclusions previously discussed in the literature, such as the conclusion that more developed countries reap higher benefits from financial development and the result that the benefits from financial development are larger in economies where the financial system is market-based.

The outline of the chapter is as follows. Section 2.2 provides a brief review of the related literature. In sections 2.3 and 2.4 we present the model and the data, respectively. The main results are discussed in section 2.5, while section 2.6 reports the results of robustness checks. Section 2.7 concludes the chapter.

2.2 Related Work

This chapter is related to several strands of the literature, the first being about the definition and measurement of financial development. The effort to build proper databases for the analysis of financial development is clear within this literature. An example of this is the database described in Beck et al. (2010), which includes a set of variables that measure several different aspects of financial systems and financial integration. Another effort to build a database which makes possible the comparison of countries in terms of financial development is the Global "Financial Development database" (Cihak et al., 2013). The authors define financial development as "improvements in the quality of five key financial functions: (1) producing and processing information about possible investments and allocating capital based on these assessments; (2) monitoring individuals and firms and exerting corporate governance after allocating capital; (3) facilitating the trading, diversification, and management of risk; (4) mobilizing and pooling savings; and (5) easing the exchange of goods, services, and financial instruments"(p.5). That paper, and the database it describes, focuses on measuring financial development by four characteristics of financial systems: depth, access, efficiency and stability. The need for a more general measure of financial development for use in empirical work has been addressed by Svirydzenka (2016). The set of indices presented in that paper measures several dimensions of financial development, and includes a broad index that attempts to measure the general state of financial development of each country.

The second strand of the literature to which our work is related is the one concerning the role of the financial system in the economy. The main view in the literature is that the financial system is the facilitator of the allocation and deployment of economic resources in an economy where outcomes are uncertain, and should take on all the functions that come with this particular role, as stated by the seminal work by Merton (1992). The question of whether or not the financial system is doing more harm than good is addressed in Zingales (2015). The role of the financial system is emphasized in applied work which finds evidence not only that shocks originated from outside the financial sector can be amplified through it—possibly causing a recession (Stock and Watson, 2012)—but also that shocks within the financial system can affect economic outcomes (Gilchrist and Zakrajšek, 2012, and Caldara et al., 2016) and do have spillover effects across countries (Ciccarelli et al., 2012). This has led to an analysis of what would be the best practice in terms of financial systems and to how deviations from it can impact on a country's economic development (Greenwood et al., 2013).

Related results can also be found in the literature on the relation between financial development and crises, which has been analyzed with great attention in the past few years, for example in Bordo and Meissner (2015). This literature has found evidence that links deeper financial systems with reduced volatility of output, consumption and investment—see, e.g., Dabla-Norris and Srivisal (2013). The model of Gennaioli et al. (2014) shows that financial development may provide stronger incentives for governments to avoid defaulting and to have better discipline on macroeconomic policies. However, as Jordà et al. (2011) find, financial development might make financial crises more likely by promoting credit growth.

The last part of the literature to which this chapter relates focuses on finding the effect of financial development over specific macroeconomic variables, with a considerable amount of effort being devoted to the debate about the effects on GDP growth. While some authors consider that there may not be any (significant) effect (e.g. Lucas, 1988 states that financial matters are "over-stressed", although admitting that the lack of sophistication of financial institutions works as a limiting factor on economic development), the general consensus it that there seems to be a link between financial development and economic growth. An example of the latter is found in Valickova et al. (2015), which also provides a set of possible measures and proxies for financial development.

Several techniques have been employed to study the impact of financial development on growth, such as the cross-section and dynamic panel data techniques from Beck et al. (2000). Empirical research has also attempted to identify the channels through which financial development affects growth. There is evidence suggesting that is comes from a better allocation of capital (Wurgler, 2000), from greater returns on capital (Greenwood and Jovanovic, 1990) and from the reduction of the costs of external financing of firms via the reduction of financial market imperfections (Rajan and Zingales, 1998). This analysis has been carried out considering different aspects of financial development; for example, Beck and Levine (2004) consider both stock market development and bank development as measures of financial development and relate them to economic growth. It is worth mentioning that the literature also finds it plausible that economic growth itself boosts financial development (Greenwood and Jovanovic, 1990; Smith and Boyd, 1998).

The literature on the effects of financial development on other macroeconomic variables is diverse. There are studies that focus on the links with investment and from there with GDP growth (Xu, 2000), with foreign direct investment (Desbordes and Wei, 2017), with exports (Chaney, 2016), with the number of destinations one country is capable of exporting to (Chan and Manova, 2015), with total factor productivity and rates of factor accumulation (Benhabib and Spiegel, 2000), with the tendency for currency appreciation caused by remittances (Acosta et al., 2009) and with its impact over the way exchange rate volatility impacts the rest of the economy (Aghion et al., 2009). The effect over consumption has also been documented, especially it variation across "good times", financial crises and bubble episodes (Maggiori, 2017; Carvalho et al., 2012). The model in Guerrieri and Lorenzoni (2017) links shocks in the financial sector to consumption decisions and their consequences for GDP and the interest rate.

2.3 Model and Methodology

The model we use to study the link between core macroeconomic variables and financial development is a PVAR. A PVAR of order p may be written as:

$$\boldsymbol{y}_{i,t} = \boldsymbol{A}_{0i} + \sum_{l=1}^{p} \boldsymbol{A}_{1l}\boldsymbol{y}_{i,t-l} + \boldsymbol{A}_2\boldsymbol{x}_{i,t} + \boldsymbol{A}_3\boldsymbol{s}_{i,t} + \boldsymbol{\epsilon}_{i,t} \tag{2.1}$$

where $\boldsymbol{y}_{i,t}$ is an $m \times 1$ vector of endogenous variables for the ith cross-sectional unit at time t, $\boldsymbol{x}_{i,t}$ is a $k \times 1$ vector of predetermined variables, $\boldsymbol{s}_{i,t}$ is an $n \times 1$ vector of strictly exogenous variables and $\boldsymbol{\epsilon}_{i,t}$ is the error vector, which we assume to be well behaved.

In our model, the vector of endogenous variables, $\boldsymbol{y}_{i,t}$, is the following:

$$\boldsymbol{y}_{i,t} = (d\_l\_FD_{i,t}, d\_l\_Y_{i,t}, d\_l\_C_{i,t}, d\_l\_I_{i,t}, d\_l\_P_{i,t}, d\_l\_MR_{i,t}, d\_r_{i,t}, d\_l\_e_{i,t})' \tag{2.2}$$

In equation (2.2), d_l_Y is GDP's growth rate, d_l_C is consumption's growth rate, d_l_I is investment's growth rate, d_l_e is the exchange rate's growth rate, d_l_P is the inflation rate, d_r is the first difference of the interest rate, d_l_MR is the growth rate of the monetary aggregate and d_l_FD is the growth rate of the financial development index. This choice of variables is based on the global VAR (GVAR) models of Pesaran et al. (2004) and Dees et al. (2007). Given the focus of our study, we add investment, consumption and financial development to the list of endogenous variables in those models.

The coefficient matrices in equation (2.1) are $\boldsymbol{A}_{0i}$ ($m \times 1$), $\boldsymbol{A}_{1l}$ ($m \times m$, for $l = 1, \ldots, p$), $\boldsymbol{A}_2$ ($m \times k$) and $\boldsymbol{A}_3$ ($m \times n$). Note that the vector of constants ($\boldsymbol{A}_{0i}$) is allowed to be specific to each cross-sectional unit. As is well known (Nickell, 1981), fixed-effects estimates will be biased. Here we estimate the coefficients of the model using equation by equation Generalized Method of Moments (GMM, see Hansen, 1982). We deal with the fixed effects by using a forward orthogonal deviations transformation, as proposed by Arellano and Bover (1995). This transformation subtracts to each observation the average of the future observations. Specifically, the transformation $u^*_{i,t}$ of the variable $u_{i,t}$ is obtained through:

$$u^*_{i,t} = c_t \left[u_{i,t} - \frac{1}{(T-t)}(u_{i,(t+1)} + \cdots + u_{i,T}) \right], \quad t = 1, \ldots, T-1 \tag{2.3}$$

where $c_t^2 = (T-t)/(T-t+1)$. We use the lags of the untransformed variables as instruments for the lags of the transformed variables. A consequence of the use of the model and moment selection criteria—see below—, which require overidentification, is that we will be using a greater number of lags as instruments than the number of lags we include for the transformed variables in the model.

The methodology we use for this model follows closely the one described in Abrigo and Love (2016). We start by choosing an appropriate lag order for our PVAR model. In order to do this, the procedure makes use of the model and moment selection criteria proposed by Andrews and Lu (2001). Note that these criteria can only be computed for models in which the number of moment conditions is greater than the number of endogenous variables. The version of the Bayesian information criterion (BIC, see Schwarz, 1978) used in the procedure is calculated as follows for a PVAR(p) with k variables, q lags for instruments and sample size n:

$$MBIC = J_n - (q - p)k^2 \ln n \tag{2.4}$$

where J_n is the J statistic for the overidentifying restrictions associated with the PVAR model of order p with k variables and using q lags in the instruments.

After selecting and estimating the PVAR model we check for stability and then proceed towards Granger causality tests (Granger, 1969) and impulse response functions (IRF).

2.4 Data

Our choice for the variables is the following: for consumption we use household consumption expenditures in 2005 US dollars; for GDP we use GDP in 2005 US dollars; for investment we use gross fixed capital formation in 2005 US dollars; as a measure of prices we use the consumer price index; our measure of the real interest rate is obtained by adjusting the nominal interest rate for inflation; our measure of the exchange rate is the real effective exchange rate; for financial development we use a broad financial development index; and for money we use the ratio of broad money to GDP.

Our dataset contains yearly observations from 1981 to 2013 for the 36 countries listed in Table 2.1. Table 2.2 presents the descriptive statistics of our variables. The correlation matrix is in Table 2.3.

The data for GDP, household consumption expenditures and investment were obtained from the United Nations National Accounts Main Aggregates Database. The real effective exchange rate was collected from the World Bank online database. The consumer price index was also collected from the World Bank, except in the case of the United Kingdom (for which the series was retrieved from the AMECO online database). The real interest rates were obtained by adjusting nominal interest rates for inflation. For most of the countries in our sample, the nominal interest rates were obtained from the World Bank (lending rate). For Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Portugal, Spain, United Kingdom and United States of America, the interest rate data comes from AMECO. For New Zealand, Switzerland and Norway we use the 90-day interbank rates from the Federal Reserve Economic Database (FRED). The data for the broad money to GDP

Table 2.1: List of countries in the dataset

Australia	Austria
Bahamas	Belgium
Bolivia	Canada
Denmark	Dominica
Finland	France
Gambia	Germany
Greece	Grenada
Iceland	Ireland
Italy	Japan
Malawi	Netherlands
New Zealand	Nigeria
Norway	Papua New Guinea
Philippines	Portugal
Saint Lucia	Singapore
South Africa	Spain
St.Vincent and the Grenadines	Switzerland
Trinidad and Tobago	United Kingdom
United States of America	Uruguay

Table 2.2: Descriptive statistics

Variables	N	mean	s.d.	min	max
d_r	1,188	0.00116	0.0557	-0.585	0.864
d_l_C	1,188	0.0253	0.0541	-0.281	0.514
d_l_Y	1,188	0.0261	0.0332	-0.123	0.193
d_l_I	1,188	0.0228	0.145	-1.876	1.718
d_l_P	1,188	0.0678	0.185	-0.354	4.775
d_l_e	1,188	-0.00264	0.0963	-1.356	0.615
d_l_MR	1,188	0.0463	0.103	-0.646	1.461
d_l_fd	1,188	0.0140	0.0769	-0.424	0.419

Notes: The variables are identified in the text. “N” is the number of observations. “s.d.” is the standard deviation.

Table 2.3: Cross-correlation table

Variables	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	1.000							
d_r	-0.010	1.000						
d_l_MR	0.004	0.118	1.000					
d_l_P	0.092	-0.139	-0.207	1.000				
d_l_I	0.053	0.050	0.061	-0.004	1.000			
d_l_C	0.086	0.045	0.095	-0.021	0.042	1.000		
d_l_Y	0.059	0.035	0.217	-0.083	0.418	0.413	1.000	
d_l_fd	0.044	-0.036	0.156	-0.146	0.016	0.067	-0.001	1.000

Notes: The variables are identified in the text.

ratio was obtained from the World Bank, except for Austria, Finland, France, Greece, Ireland, Netherlands, Portugal, Spain, Canada and New Zealand (the series for these countries come from FRED) and for Belgium and Germany (the data is from Datastream).

For financial development we use the broad-based index of financial development provided by Svirydzenka (2016). The broad index of financial development which we use is the final aggregation level of a series of subindices computed in Svirydzenka (2016). The procedure starts by applying principal component analysis to a set of financial system data in order to obtain a measure of efficiency, a measure of access and a measure of depth for both the financial markets and the financial institutions of a given country. In the intermediate step, the measures of efficiency, access and depth are aggregated for financial markets and for financial institutions. This produces two indicators, one of the development level of the financial markets and the other of the development level of financial institutions. The last step aggregates these two indices in order to obtain the broad-based index of financial development, which reflects the development of the financial system of a country.

We believe that the usage of a general indicator of financial development has benefits for understanding the true nature of its impact on economic outcomes. The typical indicators of financial development tend to focus on just one aspect of the whole process, like the size of markets, or specific changes to the institutional framework. Focusing on a single aspect of the process might lead us to thinking that it has gone too far (like the ”too much finance” result in the literature) when in fact it can be just one fraction of the whole process which went too far, leaving space for further improvements in the financial systems which can be beneficial to the economy. This indicator is also interesting because it is available for a large number of countries over a relatively large time span. In the robustness checks section we study the impact of different financial development indicators, as well as what happens when we consider only financial market or financial institution development.

2.5 Results

The following sections report the main results of our estimations on the PVAR model. These estimations are done primarily through the *pvar* command (Abrigo and Love (2016)) for the Stata (StataCorp (2017)) econometric software.

2.5.1 Lag selection

We choose the lag order of our PVAR model by applying the procedure described in Andrews and Lu (2001). The procedure is the following. We check a given set of lag orders for the models by imposing that the number of instruments used for estimating each of the models in a given set is the order of the largest model plus one. We want a model that does not reject the null for Hansen's J test and also minimizes the model and moment selection criteria. Additionally, we also do model and moment selection for the case without financial development in the variable list. We are interested in a combination of lag order and number of instruments that meets the conditions above in both the model with financial development and the one without it. Table 2.4 shows the computed model and moment selection criteria.

Table 2.4: Model selection for the benchmark model

	With d_l_fd			Without d_l_fd		
Order - Inst.	J pvalue	MBIC	MBIC*	J pvalue	MBIC	MBIC*
1 - 2 lags	0.302	−377.659	−359.186	0.169	−283.89	−271.81
1 - 3 lags	0.052	−734.611	−721.312	0.066	−561.358	−556.807
2 - 3 lags	0.08	−364.351	−357.382	0.344	−288.196	−281.247
1 - 4 lags	0.028	−1096.739	−1096.739	0.013	−828.779	−828.779
2 - 4 lags	0.055	−730.668	−730.668	0.078	−559.281	−559.281
3 - 4 lags	0.221	−370.227	−370.227	0.093	−276.379	−276.379

The MBIC* is calculated imposing the exact same sample for all models. In this case, it is the sample which would be used for the PVAR(3) with 4 lags in the instruments. This allows us to compare the MBIC for these models.

We start by imposing that the number of lags for the instruments be equal to two, and testing the PVAR(1) model for both cases (with and without financial development). The Hansen J test fails to reject the null for both models with p-values above 0.1. Next we impose that the number of lags for the instruments be equal to three, which allows us to compare a PVAR(1) against a PVAR(2). In the case of the model with financial development we have a p-value of 0.052 for the PVAR(1) and 0.08 for the PVAR(2). Without financial development in the model, we have a p-value of 0.066 for the PVAR(1) and a p-value larger than 0.1 for the PVAR(2). The PVAR(1) is the one which minimizes the information criteria for this case.

We then impose four as the number of lags for the instruments, and compare a PVAR(1) with a PVAR(2) and a PVAR(3). Here, the PVAR(1) rejects the null of Hansen's J test, both with and without financial development. When the models include financial development, the PVAR(3) has a p-value above 0.1 while the PVAR(2) has a pvalue of 0.055. When the models do not include financial development, the PVAR(3) has a p-value of 0.09, while the PVAR(2) has a p-value of 0.08. When the number of lags for the instruments is four, the model which minimizes the information criterion and does not reject the null of the J test is the PVAR(2) regardless of whether we include financial development or not.

We will use the PVAR(1) with two lags in the instruments in the remaining sections, essentially because it is the one where the p-value of the J test for both the model with and without financial development is above 0.1. In section 2.6 we assess the sensitivity of the results to the lag order. The PVAR(1) with two lags for the instruments has all eigenvalues within the unit circle, so that the estimated model is stable and the (non-accumulated) impulse-response functions will converge to zero.

2.5.2 Granger Causality

The p-values for the Granger-causality tests are shown in Table 2.5.

The Granger causality analysis indicates that within our data sample we cannot put aside the possibility that the financial development index has a role in our model. In fact, we reject the null that financial development has no impact in the equations for inflation, investment and GDP. Additionally, the fact that we do not reject the null for the exchange rate, the real interest rate and inflation in the equation for the financial development index also supports the finding that financial development has a role to play in the model. The nature of the variables that have an impact on the financial development index and the nature of the variables on which the financial development index has an impact hints at a possible mechanism for financial development to have an effect on the economy.

Table 2.5: Granger causality tests

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.002	0.760	0.000	0.059	0.066	0.010	0.0004
d_r	0.116	NA	0.002	0.000	0.318	0.650	0.585	0.011
d_l_MR	0.384	0.162	NA	0.069	0.235	0.539	0.590	0.338
d_l_P	0.043	0.000	0.000	NA	0.076	0.356	0.155	0.000
d_l_I	0.110	0.327	0.389	0.589	NA	0.722	0.834	0.053
d_l_C	0.640	0.323	0.611	0.265	0.174	NA	0.082	0.847
d_l_Y	0.700	0.724	0.001	0.962	0.000	0.000	NA	0.295
d_l_fd	0.107	0.453	0.092	0.027	0.001	0.672	0.000	NA
ALL	0.019	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

2.5.3 Impulse Response Analysis

We now turn to an impulse response function analysis. Our first step here is to choose an order for the variables in our PVAR model, to use when we apply the Choleski decomposition. We use the following order for our variables: financial development, GDP, consumption, investment, prices, monetary aggregate, interest rate and exchange rate.

As a preliminary robustness check, we compared our benchmark model with a PVAR that does not include the financial development index. Overall, the inclusion of the growth rate of the financial development index does not cause any major changes in the behavior of the impulse response functions. The general effect is that the inclusion of financial development in the model tends to smooth the impulse response functions as they converge to zero.

We now assess the impact of a shock to financial development on the variables in the PVAR — see Figures 2.1 and 2.2. An impulse to financial development has a noticeable positive effect over investment and GDP. The effect over consumption and the monetary aggregate is positive, but the confidence intervals are rather large. Nevertheless, in cumulative terms, the confidence interval for consumption includes zero at one point while the confidence interval for the monetary aggregate does not. The effect on the interest rate, inflation, and the exchange rate is non significant as the confidence interval includes zero in both the normal IRF and the cumulative one.

The responses of financial development — Figures 2.3 and 2.4 — to impulses to the other

Figure 2.1: IRF, impulse on Financial Development

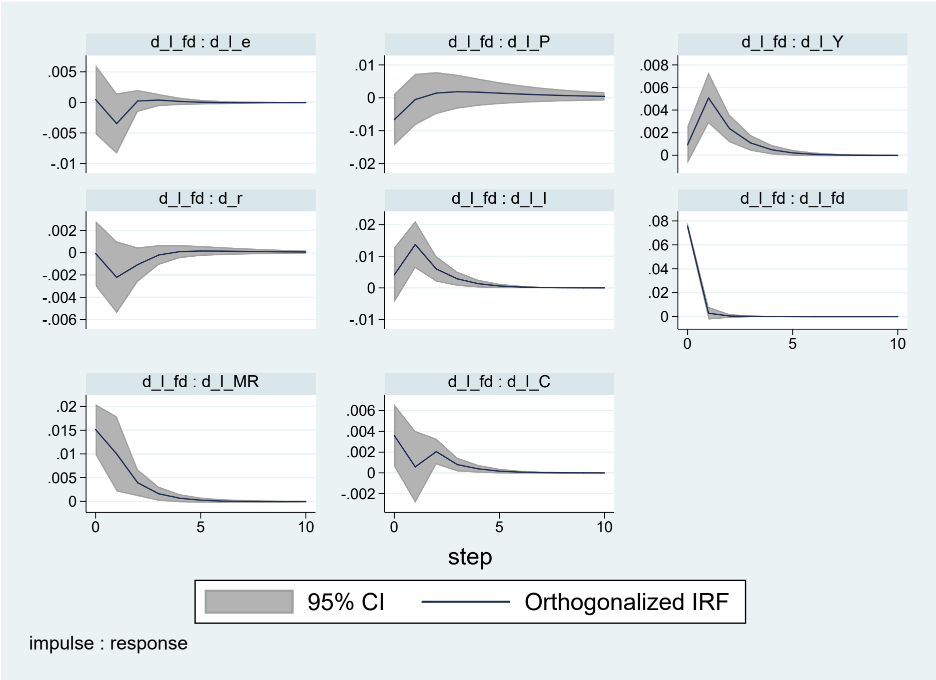


Figure 2.2: IRF, impulse on Financial Development, cumulative

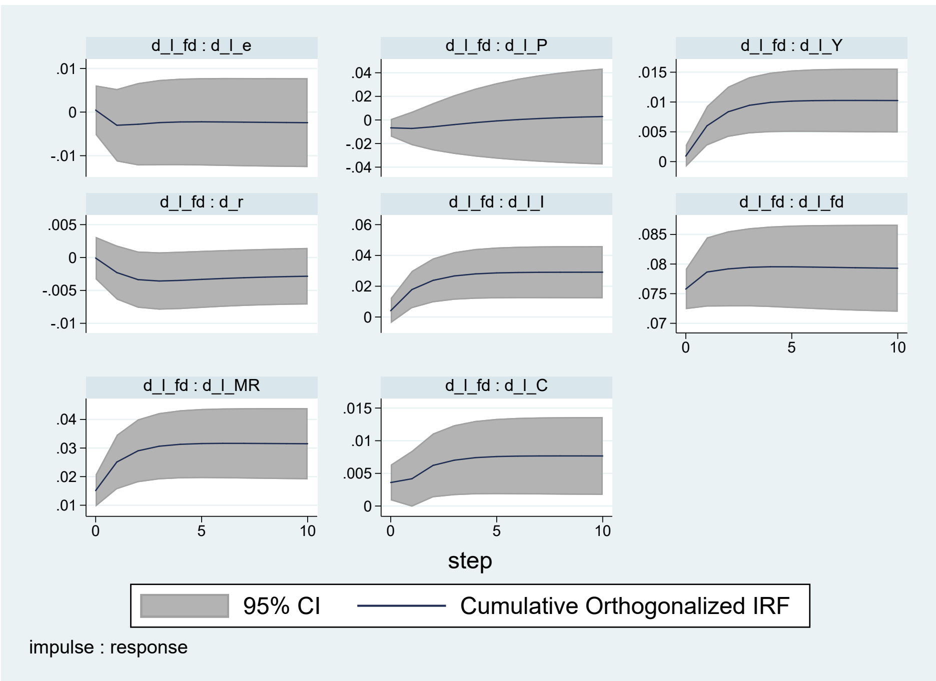
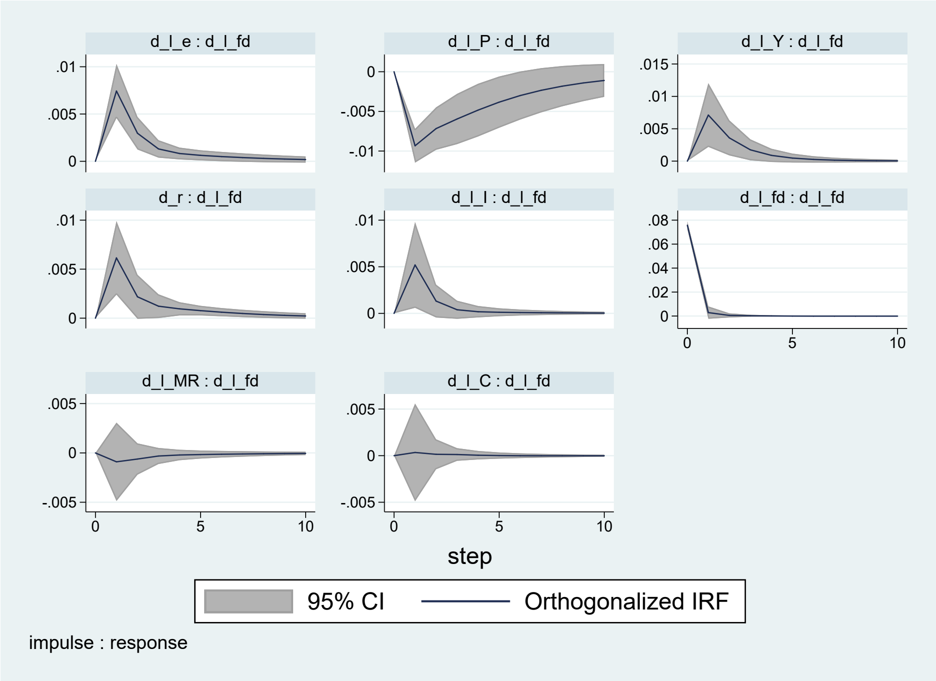


Figure 2.3: IRF, response of Financial Development



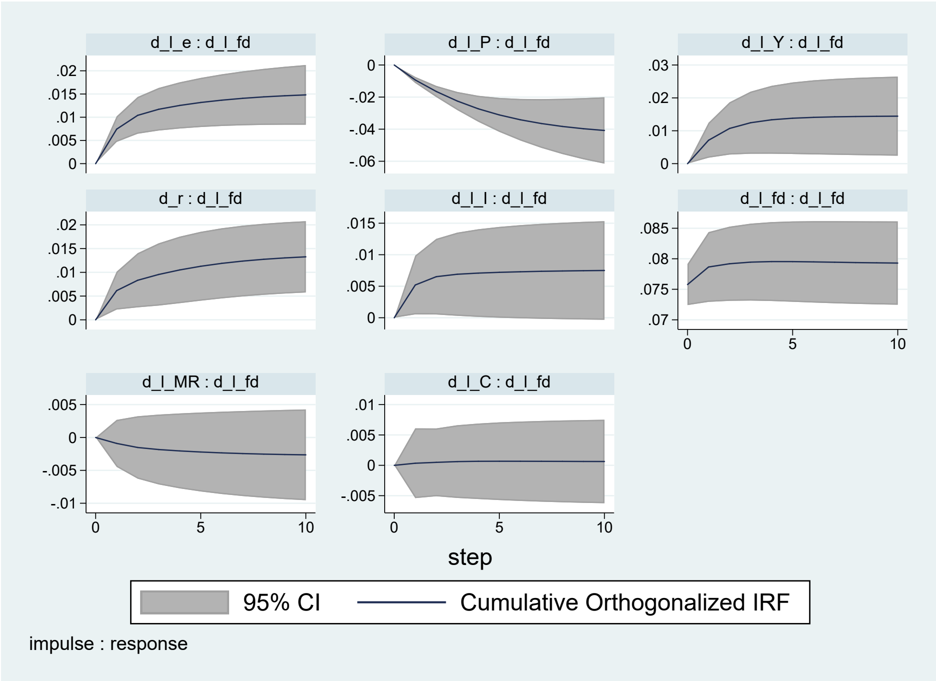
variables show that the variables which have a positive effect on financial development are the interest rate and the exchange rate. Investment, consumption and GDP seem to have a positive effect but the confidence intervals include zero for most of the periods. The accumulated effects of shocks to investment and consumption do not seem to be significant for financial development. On the other hand, shocks to GDP appear to influence financial development positively, while shocks to inflation have a negative impact.

Overall we see that the effects displayed in the impulse responses are relatively short lived. Nevertheless, the results indicate that financial development plays a role as a mechanism that connects the financial sector and the macroeconomic aggregates, carrying shocks from the financial sector to the rest of the economy and also receiving shocks from the rest of the economy.

2.6 Robustness Checks

In order to verify if our results are solid we perform a series of robustness checks. The battery of checks we use includes the traditional changing of the order of the variables in the PVAR system, and also other experiments aimed at finding nonlinearities in the effects of financial development on other macroeconomic variables.

Figure 2.4: IRF, response of Financial Development, cumulative



2.6.1 Ordering of Variables and different PVAR models

When using PVAR models two decisions that may have a large impact on the results are the ordering of variables and the lag order of the PVAR model. We now assess how different our results would be had we used different choices for the ordering for our variables and for the number of lags.

Regarding the ordering of the variables, we tested a set of different orderings of variables, including completely reversing the order of the variables, switching the places of a slow reaction variable and of a fast reaction one, switching the order of slow reaction variables, and switching the order of fast reaction variables. The bulk of the results remains the same, with the signs of the effects unchanged and only the behavior of the impulse response functions changing slightly.

Regarding the number of lags in the PVAR model, we analyzed the results obtained from the other PVAR models that our model selection criteria indicated as possible alternatives to our benchmark model — recall section 2.5, namely Table 2.4. Those models are the PVAR(1) with 3 lags in the instruments and the PVAR(2) with 4 lags in the instruments. In both cases, the main conclusions of the analysis remain the same as in the benchmark model.

2.6.2 The crisis period

Advanced economies have been strongly hit by the international financial crisis and then by the Eurozone's sovereign debt crisis. This period of crisis may have some influence on our results and therefore we control for it in two ways. The first way is to remove the observations from the period between 2008 and 2013. The second method we use to control for the crisis period is by including a dummy variable in our model, which takes the value 1 for the years ranging from 2008 to 2013 and 0 in all the other years. Our purpose here is to see if these years are what drives our results or if they just fall in line with the results that we reported in the previous sections. To be comparable to what we did previously, we will be estimating a PVAR(1) with two lags for the instruments.

Depending on how we control for the crisis, some of our results from the benchmark model disappear, namely the positive effect of financial development on GDP and consumption in the case where we restrict the sample. This suggests that during the crisis the link between the financial sector and the rest of the economy was very strong, stronger than in ”normal times”. Overall, when controlling for the crisis period, we find that our results regarding the impact of financial development on investment are robust, but the results regarding the impact of financial development on consumption and GDP become weaker. The tables for the Granger causality tests and the IRF plots can be found in appendices B.2.1 and B.2.2.

2.6.3 The level of financial development

We also take into account the fact that our results may mask differences in behaviour across countries. Namely, the relation between financial development and the rest of the economy may not be the same for all countries, regardless of their level of financial development. The possibility of a non-linearity in the effects of financial development has been documented in the literature. The effect has been shown to decline over time in response to the aftermath of the financial crisis (Rousseau and Wachtel, 2011), and that there is a threshold (Arcand et al., 2015) which coupled with decreasing marginal benefits can lead to potentially negative effects during crises (Breitenlechner et al., 2015), and even to a negative effect on stability for high levels of financial development (Sahay et al., 2015).

To assess the importance for our results of non-linearities related to the level of financial development we take two approaches. The first is based on a split of the sample. The second is based on the inclusion of an additional regressor in the model.

The first approach splits the sample according to the level of overall financial development. We separate the countries in two groups, one showing a high level of financial development and the other showing a low level. We define the groups according to a threshold value. The countries that in the year 2007 had a lower value of financial development than the threshold value are considered to have a low financial development level. We experiment with two different values for this threshold: 0.52 and 0.68. These values are suggested by a threshold fixed-effects panel regression performed on each of the equations of a PVAR(1) with a specification equal to the one we use for our benchmark model.

To be concrete, our procedure for obtaining sensible values for the thresholds is the following. We apply the procedure of Hansen (1999) to each of the equations corresponding to our PVAR model. For example, considering the equation for consumption, we estimate the model:

$$d\_l\_C_{i,t} = \mu_i + \beta_1' x_{i,t-1} I(FD_{i,t} \leq \gamma_C) + \beta_2' x_{i,t-1} I(FD_{i,t} > \gamma_C)$$

where I($\cdot$) is the indicator function and

$$x_{i,t} = \begin{bmatrix} d\_l\_Y_{i,t} & d\_l\_I_{i,t} & d\_l\_e_{i,t} & d\_l\_P_{i,t} & d\_r_{i,t} & d\_l\_MR_{i,t} & d\_l\_FD_{i,t} \end{bmatrix}'$$

Estimation of these models yields estimates of the threshold parameter, γ, for each equation. These give us an indication as to where we should split our sample. Based on those estimates, we decided to split the sample at either 0.52 or 0.68.

The results from using these threshold values to split the sample are very similar, with the Granger causality tests indicating an effect of financial development on the monetary aggregate in the countries with low financial development levels and an effect on investment, consumption and GDP in the group with high levels of financial development. The impulse response functions show that these effects are positive and significant. These results point to the existence of a nonlinear effect of financial development on the macroeconomic variables in the model.

The second method we use to assess the role of the level of financial development works by including the log of the lagged level of financial development in the model. The inclusion of this additional variable does very little to change our results from the benchmark model, aside from a few minor differences in the behaviour of the impulse response functions.

2.6.4 Alternative Measures of Financial Development

The literature on financial development and its effects on the economy has been around for a while. Several ways of measuring the financial system and its development have been suggested over the years. In this section we redo the analysis using some of these measures instead of the broad index of financial development used in the previous sections.

The measures we use are the ratio of private credit by deposit money banks and other financial institutions to GDP, stock market capitalization to GDP and stock market total value traded to GDP.

The data on the ratio of private credit by deposit money banks and other financial institutions to GDP is from the World Bank's Global Financial Development Database for all countries except for Belgium, France and the Netherlands (for which the data comes from the FRED online database). The data for the Stock Market capitalization to GDP ratio comes from the Wold Bank's Global Financial Development Database for all countries except Belgium, France, Netherlands and South Africa, for which the source of the data is the FRED database. The data for the Stock Market Total Value Traded to GDP comes from the World Bank's Global Financial Development Database for all countries but Switzerland, for which we retrieved the data from the FRED online database.

Given the data available, for ensuring comparability between the results obtained with the different measures, in this section we estimated the models (including the benchmark model) on a sample with 22 countries covering the period from 1989 to 2012. The list of countries in this analysis is presented in Table 2.6.

Table 2.6: Reduced list of countries

Australia	Austria
Belgium	Denmark
Finland	France
Germany	Greece
Italy	Japan
Netherlands	Nigeria
Norway	Philippines
Portugal	Singapore
South Africa	Spain
Switzerland	Trinidad and Tobago
United Kingdom	United States

While the Granger causality analysis does not change much, we obtain different results according to the proxy of financial development we use for the impulse response functions. Even though different proxies for financial development can be linked to effects on roughly the same variables, the impulse response functions for the different proxies show different magnitudes and profiles. The differences between the effects in the low and high financial development groups also change according to the variable we chose to proxy financial development with. In the case of stock market total value traded, we estimate a much more pronounced effect of the financial development proxy on most of the other variables in the high financial development group; this is the opposite of the benchmark case. Overall, the results for stock market capitalization are very close to the ones obtained using the broad financial development index. The results for stock market total value traded and private credit by deposit banks and other financial institutions to GDP display minor differences relatively to the benchmark, possibly reflecting the importance of different aspects of financial development.

2.6.5 Financial Structure

In the literature there is a debate on the impact of financial structure on growth—see, e.g., Levine (2005). The debate gains particular importance when countries (for example, European countries) start shifting from bank-based towards more market-based systems (Zingales and Rajan, 2003). Banks and financial markets provide different services which might imply a different impact on growth as argued by Gambacorta et al. (2014); Levine and Zervos (1998). Demirgüç-Kunt et al. (2013) go as far as considering what would be an optimal financial structure and analyze how a deviation from it, in terms of market and institutional development, can have costs in for economic activity. Despite the arguments, part of the literature (e.g., Demirguc-Kunt and Maksimovic, 2002, and Levine, 2002) find that it is overall financial development and not the specific details of the financial structure that determines the effect on growth. Other papers do find that excessively leaning towards one specific kind of financial system (bank based in the case) can be linked to lower economic growth (Langfield and Pagano, 2016).

In line with this literature, we allow for different aspects of the process of financial development to have different effects on the economy. To do this we look at how the results change when we redo the previous analysis using separate measures for the development of financial markets and for the development of financial institutions. The results for these estimations are shown in appendices B.5 to B.7. When using the sub-indices for financial markets and financial institutions instead of the global financial development index we lose three countries from our original sample due to missing data. The countries are Dominica, Gambia and St.Vincent and the Grenadines.

Some differences can be seen in the results obtained by using each of the measures. Namely, when we use a measure of the development of financial institutions, the effect of financial development on the other variables is less noticeable. When we split the sample according to the level of financial development, both measures of financial development appear to be of little importance in the low-development group. However, for the high-development group the positive effect on GDP, investment and consumption detected in the benchmark analysis becomes stronger when measuring financial development with the indicator of financial market development.

We also experiment splitting the sample between countries where financial intermediation is relatively more market based and countries where it is relatively more bank (or institution) based. In order to split the sample we divide the index of financial market development in the year 2007 by the index of financial institution development in the year 2007 and consider the countries for which this ratio is 1 or above as market based, and otherwise as institution based. Regarding the way in which we are measuring financial structure, one has to point out that this proxy reflects the relative development of financial markets in terms of financial institutions. The main implication of this is that one might have a country which is classified as market based not because it has highly developed markets but because its institutions are in a lower state of development. Our results suggest that the effect of financial development on the rest of the economy is very similar for both groups, although it is much more noticeable in the market-based group.

2.6.6 Economic Development and Doing Business Index

The macroeconomic environment per se might also be a crucial factor in determining what is the effect of financial development on macroeconomic variables. To take this possibility into account, we consider two variables on which to split our sample: GDP per capita and the Doing Business Index and report the results in appendices B.8 and B.9.

The first, GDP per capita, reflects overall economic development. In this case the countries are separated according to whether their GDP per capita in 2007 is below or above the sample mean for year 2007. In this case, the Granger causality tests give the same kind of nonlinearity as the split based on the level of financial development, with financial development in the low-GDP group having an effect on monetary aggregate and having an effect over investment, GDP and consumption in the high-GDP group. The signs of these effects are positive. Some caution must be taken when linking these results with the ones regarding the level of financial development, as there is a high degree of correlation, approximately 0.8, between GDP per capita and the log of the financial development broad index in our sample.

The second criterion for splitting the sample, the Doing Business Index, is an indicator of how easy it is to conduct business activities in a given country. We use the distance to frontier (DTF) of the Doing Business Report, which measures how far the economy is from the best practices in the items considered in the Report. DTF is available from 2009 to 2013. We split the countries according to whether they have a DTF index in 2013 below or above the average for all countries and all years. The results we obtain in this case are similar to our results. They suggest that financial development may play a different role in an economy according to how easy it is to create and run a firm in that country. The group further to the frontier shows a positive effect of financial development on the monetary aggregate, while the group closer to the frontier shows a positive effect on the monetary aggregate, GDP, investment and consumption.

2.6.7 Oil Prices

The prices of oil have had a large importance in modern economies in recent decades. We control for this fact by including oil prices as an exogenous variable in our PVAR estimations, and report the results in appendix B.10. We use two series of oil prices for this analysis. The first is annual data, from 1980 to 2013, from the series ”Global Price of Brent Crude” from the FRED online database. The second is also annual, from 1980 to 2013, and is the series ”Global price of WTI Crude” from the FRED online database.

Compared to the baseline model, the main differences are that, in the Granger causality analysis, the test of the significance of financial development in the equation of prices doesn’t reject the null, and the rejection of the null in the equation for the monetary aggregate in the low-development group is now less strong. Aside from these differences and a few changes to the behavior of the impulse response functions and their confidence intervals, the results are the same as with the main results from our baseline model.

2.7 Conclusion

In this chapter, we used a Panel VAR methodology together with a new broad index of financial development to study the relation between financial development and macroeconomic variables.

Our results help shed light on the debate concerning the links between financial sector development and economic growth. We find evidence supporting the finance-growth nexus view of financial development, where financial development leads economic growth, with financial development having a positive impact on both investment and GDP. This result is robust to different specifications, although it may be influenced by the period following the international financial crisis. Additionally we find some evidence that there may be a link between financial development and consumption, namely a positive effect of financial development on consumption.

Another debate from the literature with which this chapter related is the debate on the direction of the causality between financial development and growth. Our results seem to favor the argument that the causality link flows from financial development to economic growth, following the evidence from King and Levine (1993); Rousseau and Wachtel (1998) and Rousseau and Wachtel (2000), rather than the bi-directional causality link argued by Calderón and Liu (2003); Luintel and Khan (1999) and Arestis et al. (2001). In fact, we find strong evidence of an effect over investment and to some degree GDP growth, similar to the results from Fuchs-Schündeln and Funke (2003), but much less noticeable evidence of an effect going from GDP to financial development.

Our results also suggest that the effects of financial development may not be linear. We find evidence of this when we split the sample between low and high financial development countries, when we split according to economic development, when we split according to the doing business index and even when we consider financial structure. Essentially, the results obtained when we split the sample show that financial development has a stronger impact on the economy in more advanced economies.

Chapter 3

Financial Development and Consumption Adjustment under Smooth Transition

3.1 Introduction

The events of the past two decades make a statement about the non-ignorability of the financial system and its crises. Over the years it has become clear that what happens inside the financial sector has relevant effects on other areas of the economy and on the daily lives of the population. This implies that the way we study the behavior of macroeconomic variables may have to account for how the financial system connects to these variables. Consumption, as one of the main macroeconomic variables, should be paid special attention. In this chapter we try to find evidence of a possible link going from financial development to aggregate consumption. In particular, we want to evaluate the reaction of consumption to changes in the level of financial development.

While mainstream consumption theory, such as Modigliani and Brumberg (1954), Friedman (1957), Hall (1978), Flavin (1981) and Mankiw and Shapiro (1985), provides little support for a direct impact of financial development on consumption behavior, it is possible to envisage circumstances in which an indirect effect can exist. As stated by Deaton (1992), a large portion of consumption theory is built upon the theory of inter-temporal choice and optimization and rests on the assumption that the consumer is able to move funds across different time periods. This transfer of funds is done primarily through the financial system and this is precisely the key to the mechanism by which financial development may affect consumption. While not a direct determinant of consumption, financial development enables the consumer to improve the allocation of resources, and to achieve a consumption level (defined by the determinants typically discussed in the literature) corresponding to higher utility. Examples of this mechanism are the reduction of consumption's excess sensitivity to income (Bandiera et al., 2000; Gilchrist and Zakrajšek, 2012) and the reduction of the intermediation costs, which can have positive effects over consumption (Antunes et al., 2013).

In this chapter we analyze how consumption's response to its determinants changes with financial development, in the spirit of Jappelli and Pistaferri (2011). To this end, we estimate a typical aggregate consumption specification, based on the Error Correction Model (Engle and Granger (1987)), and see how the coefficients in the model change with different values of financial development. The varying coefficients are estimated by means of the Panel Smooth Transition Regression estimation technique of González et al. (2017). ECM models were introduced to the literature in connection to consumption behavior and used extensivelly since then (Davidson et al., 1978; Davidson and Hendry, 1981; Nickell, 1985; Dewhurst, 1989; Hoque, 1992). The choice of this specification can be justified by the existence of constraints on how consumers allocate funds across time, as shown by Muellbauer and Lattimore (1995) for the case of credit constraints. More recent applications of ECM/cointegration models to consumption can be found in Ludwig and Sløk (2004) and Estrada et al. (2014).

We perform our estimations on a panel dataset of 46 countries with yearly observations from 2000 to 2014. Our results provide evidence that, within our dataset, financial development induces changes in the way consumption reacts to GDP and wealth in the short run, making these responses smaller, and in the way consumption adjusts towards its long-run equilibrium, making this process faster. Our results are robust to different starting values, as well as to different long-run specifications and to the inclusion of additional short-run variables.

This chapter is organized as follows. Section 3.2 describes the model used and how we estimate it. Section 3.3 presents the dataset we use. In section 3.4 we analyze the results for the panel unit root and cointegration tests. section 3.5 reports our main results. These results are checked for robustness in section 3.6. Section 3.7 offers concluding remarks.

3.2 Model and Methodology

The first subsection presents the general model that we use for consumption. The second subsection provides more technical details about the estimation and testing procedures.

3.2.1 Model Specification

The model of interest in this study is an ECM specification of consumption. We use as short-run variables the typical explanatory variables of consumption, while exploiting the possible long-run relationship between consumption, wealth and the interest rate. The benchmark model specification we use is:

$$\Delta \log C_{i,t} = \mu_i + \beta_y \Delta \log Y_{i,t-1} + \beta_r \Delta r_{i,t-1} + \beta_w \Delta \log W_{i,t-1} + \lambda z_{i,t-1} + u_{i,t} \tag{3.1}$$

where C is consumption, Y is a measure of income, r is the real interest rate, W is a measure of wealth, u is the error term, i identifies the country unit and t the time unit, and the long run component is given by:

$$z_{i,t} = \log C_{i,t} - \theta_i - \alpha_1 \log W_{i,t} - \alpha_2 r_{i,t} \tag{3.2}$$

In the context of this model, if financial development generates some kind of indirect change in consumption, we expect the parameters of the model given by equation 3.1 to vary with financial development. Our interest is then to estimate a PSTR version of this model:

$$\begin{aligned} \Delta \log C_{i,t} = \mu_i + \beta_y \Delta \log Y_{i,t-1} + \beta_r \Delta r_{i,t-1} + \beta_w \Delta \log W_{i,t-1} + \lambda z_{i,t-1} + \\ \Big[\beta_y^* \Delta \log Y_{i,t-1} + \beta_r^* \Delta r_{i,t-1} + \beta_w^* \Delta \log W_{i,t-1} + \lambda^* z_{i,t-1}\Big] g(FD_{i,t}; \gamma, c) + u_{i,t} \end{aligned} \tag{3.3}$$

with:

$$g(FD_{i,t}; \gamma, c) = \Big[1 + \exp(-\gamma \prod_{j=1}^{m} (FD_{i,t} - c_j))\Big]^{-1} \tag{3.4}$$

In the PSTR version of the model, $g(FD_{i,t}; \gamma, c)$ is the transition function, m is the number of location parameters (c_j) that we include, γ is the smoothness parameter (restricted to be positive), $FD_{i,t}$ is the threshold variable (financial development) and the coefficients with the superscript * indicate how the parameters of the model change with financial development, i.e., how the response of consumption to the other regressors changes with financial development. The actual change in the parameters as financial development evolves depends on the weight assigned to the coefficients with the superscript by the transition function. Note that the transition function takes values between zero and one—see Figure C.1 in the Appendix for an illustration. Therefore, we can think of this model has having two regimes, one corresponding to a value of zero and the other to a value of one for the transition function. When the transition function approaches zero, the relevant parameters are the ones without superscript. When the transition function approaches one, the relevant parameters correspond to the sum of the coefficients with and without superscript.

3.2.2 Panel Smooth Transition Regression

Our next step is to apply the three-stage methodology proposed by González et al. (2017) for Panel Smooth Transition Regression. The three stages of PSTR model building are specification, estimation and evaluation. We now give a brief description of each of them. The following description, based on González et al. (2017), refers to a general PSTR model with two regimes:

$$y_{i,t} = \mu_i + \beta_0' x_{i,t} + \beta_1' x_{i,t} g(q_{i,t}; \gamma, c) + u_{i,t} \tag{3.5}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, with N and T being the cross-sectional and the time dimensions, respectively. $x_{i,t}$ is a k-dimensional vector of regressors, $q_{i,t}$ is the transition variable, μ_i represents fixed individual effects and $u_{i,t}$ is the error term. The transition function $g(q_{i,t}; \gamma, c)$ is normalized to lie within zero and one. We will be using the functional form presented in equation 3.4:

$$g(q_{i,t}; \gamma, c) = \Big(1 + \exp\Big(-\gamma \prod_{j=1}^{m} (q_{i,t} - c_j)\Big)\Big)^{-1} \tag{3.6}$$

where $c = (c_1, \ldots, c_m)'$ is the vector of location parameters and γ is the (positive) parameter that controls the smoothness of the transition between the two regimes. Note that when $\gamma \to \infty$ the transition function becomes an indicator function $I(\cdot)$ and the PSTR model becomes the PTR model of Hansen (1999).

Specification

The central issue here is whether the parameter γ is different from zero. When the smoothness parameter is zero the PSTR model collapses into the linear model of the first section (equation 3.1). The ideal would be to test either $H_0 : \gamma = 0$ or $H_0' : \beta_1 = \mathbf{0}$. However, both of these tests require nonstandard procedures because some parameters are not identified under the null.

The approach taken by González et al. (2017) is to replace the transition function with its first-order Taylor expansion around $\gamma = 0$, leading to an auxiliary regression:

$$y_{i,t} = \mu_i + \beta_0'^* x_{i,t} + \beta_1'^* x_{i,t} q_{i,t} + \cdots + \beta_m'^* x_{i,t} q_{i,t}^m + u_{i,t}^* \tag{3.7}$$

where $\beta_1^*, \ldots, \beta_m^*$ are multiples of γ and $u_{i,t}^* = u_{i,t} + R_m \beta_1' x_{i,t}$, with R_m being the remainder of the Taylor expansion. Using this auxiliary regression the null hypothesis of interest ($\gamma = 0$) becomes $H_0^* : \beta_1^* = \cdots = \beta_m^* = 0$. This can be tested using a standard Lagrange Multiplier (LM - Radhakrishna Rao (1948); Silvey (1959); Breusch and Pagan (1980)) test. The LM statistic (denoted LM_χ) will be a function of the error variance-covariance matrix, for which an estimator robust to heteroskedasticity and autocorrelation may be used. Under the null, the LM_χ is asymptotically distributed as $\chi^2(mk)$.

Estimation

González et al. (2017) estimate the model by nonlinear least squares (NLS) after applying a within transformation to take care of the fixed effects.

First do the within transformation. Consider the following representation of the model:

$$y_{i,t} = \mu_i + \beta' x_{i,t}(\gamma, c) + u_{i,t} \tag{3.8}$$

where $x_{i,t}(\gamma, c) = (x'_{i,t}, x'_{i,t} g(q_{i,t}; \gamma, c))$ and $\beta = (\beta'_0, \beta'_1)'$. By subtracting the individual means one obtains:

$$\tilde{y}_{i,t} = \beta' \tilde{x}_{i,t}(\gamma, c) + \tilde{u}_{i,t} \tag{3.9}$$

where $\tilde{y}_{i,t} = y_{i,t} - \bar{y}_i$, $\tilde{x}_{i,t}(\gamma, c) = (x'_{i,t} - \bar{x}'_i, x'_{i,t} g(q_{i,t}; \gamma, c) - \bar{w}'_i(\gamma, c))'$, $\tilde{u}_{i,t} = u_{i,t} - \bar{u}_i$ and $\bar{w}_i = T^{-1} \sum_{t=1}^{T} x_{i,t} g(q_{i,t}; \gamma, c)$. The variables noted with a bar are the individual means. Note that, given γ and c, one can use equation 3.9 to estimate β. The estimate of β thus obtained will be a function of those two parameters. The NLS estimator minimizes the concentrated sum of squared errors:

$$Q^c(\gamma, c) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\tilde{y}_{i,t} - \hat{\beta}(\gamma, c)' \tilde{x}_{i,t}(\gamma, c) \right)^2 \tag{3.10}$$

where $\hat{\beta}(\gamma, c)$ is obtained by ordinary least squares (OLS) on the within-transformed model at each iteration of the nonlinear optimization.

Model Evaluation

The next stage concerns model evaluation. González et al. (2017) consider two tests, one for parameter constancy and the other for remaining heterogeneity.

The test for the null hypothesis of parameter constancy tests this hypothesis against the alternative of a Time Varying Panel Smooth Transition Regression (TV-PSTR) defined as:

$$\begin{aligned} y_{i,t} = \mu_i &+ (\beta'_{10} x_{i,t} + \beta'_{11} x_{i,t} g(q_{i,t}; \gamma_1, c_1)) \\ &+ f(t/T; \gamma_2, c_2)(\beta'_{20} x_{i,t} + \beta'_{21} x_{i,t} g(q_{i,t}; \gamma_1, c_1)) + u_{i,t} \end{aligned} \tag{3.11}$$

where $f(t/T; \gamma_2, c_2)$ is another transition function. This transition function is of the form:

$$f(t/T; \gamma_2, c_2) = \left(1 + \exp\left(-\gamma_2 \prod_{j=1}^{h} (t/T - c_{2j}) \right)\right)^{-1} \tag{3.12}$$

In this transition function $c_2 = (c_{21}, \ldots, c_{2h})'$, is a h-dimensional vector of location parameters and γ_2 is the slope parameter. The null hypothesis for the parameter constancy test is $H_0 : \gamma_2 = 0$. As before, under this null, the parameters associated with the change over time are not identified and so González et al. (2017) use a procedure similar to the one for testing the null of linearity/homogeneity (recall the section on specification, above). Again one obtains an LM_χ statistic for the null hypothesis, which is now distributed as $\chi^2(2hk)$.

Next consider the test for remaining heterogeneity. Take the model with one transition as the null hypothesis, and the model with an additional transition as the alternative, i.e.:

$$y_{i,t} = \mu_i + \beta_0' x_{i,t} + \beta_1' x_{i,t} g_1(q_{i,t}^{(1)}; \gamma_1, c_1) + \beta_2' x_{i,t} g_2(q_{i,t}^{(2)}; \gamma_2, c_2) + u_{i,t} \tag{3.13}$$

Note that the transition variable can be the same for both transitions, but that is not a requirement. The null hypothesis is $H_0 : \gamma_2 = 0$, which once more raises the issue of lack of identification of some parameters under the null. Proceeding in the same way as before to overcome this problem, González et al. (2017) derive an LM_χ statistic that has a $\chi^2(mk)$ distribution under the null.

3.3 Data

Our dataset is a panel of yearly observations, from 2000 to 2014, for 46 countries—see Table 3.1. Tables 3.2 and 3.3 report descriptive statistics and correlations, respectively.

Table 3.1: List of countries

Armenia	Australia	Austria
Belgium	Bulgaria	Canada
Chile	Cyprus	Czech Republic
Denmark	Estonia	Finland
France	Germany	Greece
Hungary	Iceland	Ireland
Israel	Italy	Jamaica
Japan	Kuwait	Latvia
Lithuania	Luxembourg	Mexico
Netherlands	New Zealand	Norway
Poland	Portugal	Republic of Korea
Romania	Russian Federation	Slovakia
Slovenia	South Africa	Spain
Sweden	Switzerland	Thailand
Ukraine	United Kingdom	United States
Venezuela		

Table 3.2: Descriptive Statistics

Variables	N	mean	sd	min	max
r	690	0.0404	0.0381	-0.0200	0.345
FD	690	0.583	0.230	0.0975	1
$\log C$	690	30.31	1.681	26.76	34.64
$\log Y$	690	30.70	1.696	26.71	34.88
$\log W$	690	27.10	1.964	22.45	31.96

Table 3.3: Cross-correlation table

Variables	$\log C$	$\log Y$	$\log W$	r	FD
$\log C$	1.000				
$\log Y$	0.995	1.000			
$\log W$	0.957	0.961	1.000		
r	-0.259	-0.273	-0.309	1.000	
FD	0.595	0.608	0.731	-0.431	1.000

The data for household consumption expenditures in constant 2010 prices in local currency was obtained from the National Accounts Main Aggregates Database (United Nations Statistics Division).

We retrieved the data for net disposable income in current local currency from AMECO for Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden, United Kingdom, Norway, Switzerland, United States, Japan, Canada, Mexico, South Korea, Australia, Bulgaria, Latvia, Lithuania, Poland, Czech Republic, Estonia, Hungary, Romania and Slovakia; from the Organisation for Economic Co-operation and Development (OECD) for South Africa, New Zealand, Chile and Russia; and for all the other countries we obtained the data from UNdata (http://data.un.org/).

Data on the interbank interest rates was collected from FRED for South Africa, Russia, New Zealand, Norway, Mexico, Israel and Iceland; from the International Monetary Fund's (IMF) International Financial Statistics for Kuwait, South Korea, Thailand, Venezuela, Chile, Jamaica, Armenia, Australia, Canada and Switzerland; and from AMECO for all the other countries.

The data for each country's total wealth in current United States dollars (USD) comes from Credit Suisse's Global Wealth Databooks.

To obtain the real interest rate we employ the usual formula:

$$\text{real rate} = \frac{1 + \text{nominal rate}}{1 + \text{inflation rate}} - 1 \tag{3.14}$$

We use data on the consumer price index obtained from the World Bank for all countries except Chile and Venezuela (for which we resorted to FRED), to compute the inflation rate.

To obtain the net disposable income and total wealth in real terms, we calculated a consumption deflator using data on consumption expenditure in current prices and consumption expenditure at constant 2010 prices. To convert in USD we use the exchange rates from the National Accounts Main Aggregates Database.

As in the previous chapter, the measure of financial development that we use is the broad-based index of financial development from Svirydzenka (2016).

3.4 Unit Root and Cointegration Tests

In this section we present the results from the panel unit root tests we ran on the variables, as well as the results from cointegration tests.

The Panel Unit Root Test we use is the CIPS proposed by Pesaran (2007), i.e., the cross-sectionally augmented IPS test, that builds on the IPS test derived by Im et al. (2003). We use one lag and consider both the case with a trend and the case without a trend. The results are in Table 3.4, The null of the CIPS test is the existence of a unit root. The failure to reject the null of a unit root in the level variables, together with the rejection of that null hypothesis for the first-differenced series, suggests that the variables are all I(1).

Table 3.4: Panel Unit Root Tests - CIPS

Variable	CIPS	p-value	CIPS - trend	p-value
$\log C_{i,t}$	-0.964	>0.1	-2.902	0.038
$\log Y_{i,t}$	-1.146	>0.1	-1.848	>0.1
$r_{i,t}$	-0.851	>0.1	-1.225	>0.1
$\log W_{i,t}$	-1.32	>0.1	-2.552	>0.1
$\Delta \log C_{i,t}$	-1.77	0.011	-2.348	>0.1
$\Delta \log Y_{i,t}$	-1.747	0.016	-1.905	>0.1
$\Delta r_{i,t}$	-2.436	<0.01	-3.035	0.018
$\Delta \log W_{i,t}$	-2.409	<0.01	-3.056	0.015

We employ two kinds of tests for cointegration. The first is the CIPS applied to the residuals of the long run regression. If the variables are in fact cointegrated, these residuals, being a linear combination of the variables, should reject the null of a unit root in this test. The second is the Westerlund (2005) variance ratio test. For both tests, the null is the absence of cointegration. The null is rejected by all the tests—see table 3.5—, though in the case of the CIPS with a trend the p-value is 0.057. The results thus point to the existence of cointegration.

Table 3.5: Panel Cointegration Test Results

CIPS	p-value	CIPS - trend	p-value	Westerlund	p-value
-1.789	<0.01	-2.8	0.057	3.2595	<0.01

3.5 Results

In this section we present the results from our estimations. We report robust standard errors for all our estimations according to the methodology of Arellano (1987). Our results were obtained using the resources available from the *plm* package for R (Croissant and Millo, 2008; Millo, 2017; Croissant and Millo, 2019) and the *PSTR* package for R (R Core Team, 2018).

3.5.1 Linear Model

We report the results for the long-run regression in Table 3.6. The estimated coefficients for the baseline ECM model are in Table 3.7. In the long-run regression, the wealth variable has a positive coefficient, which is in line with the theoretical predictions, while the interest rate coefficient has a negative sign; both coefficients are statistically significant. As for the conventional ECM estimation, the short-run coefficients of income and wealth have a positive sign and are statistically significant. The short-run coefficient for the interest rate is negative and statistically significant. The error correction component appears with the expected negative sign, and is also statistically significant.

Table 3.6: Long Run Regression Results

	$\log W_{i,t}$	$r_{i,t}$
Coefficient	0.197**	-1.688***
	(0.078)	(0.568)
R^2	0.34	

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: ECM Regression Results

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z_{i,t-1}$
Coefficient	0.204***	-0.39***	0.06***	-0.11***
	(0.04)	(0.126)	(0.009)	(0.031)
R^2		0.442		

robust standard errors in parentheses

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

3.5.2 PSTR Model

We now proceed to the PSTR approach in order to see whether the baseline model of the previous subsection neglects nonlinearities related to financial development. The results that we report in this subsection are consistent with what is considered to be the usual behavior of consumption. In other words, the response of consumption to the traditional determinants of consumption is as expected. Nevertheless, our results provide evidence of a moderating effect of financial development on the short-run response, coupled with a faster adjustment towards the long-run equilibrium when financial development is higher.

The first step when applying the PSTR model is to do the linearity test (section 3.2.2) and to choose the number of location parameters. To choose the adequate number of location parameters we use the process described by Granger and Terasvirta (1993), Teräsvirta (1994), Teräsvirta (1996) and Terasvirta et al. (2010). Therefore, we start by performing the linearity test for one, two and three location parameters. In the next step we sequentially test the parameters in equation 3.7. This sequential test is done in the following way. First we estimate the auxiliary regression with $m = 3$. Then we test that the parameters associated with the third location parameter are zero. Next we test that the coefficients associated with the second location parameter are zero given that the parameters associated with the third location parameter are also zero. Finally we test that the coefficients associated with the first location parameter are zero given that the parameters associated with the second and third location parameters are also zero. The results of these tests help us choose between the number of location parameters. Table 3.8 shows the results of these tests. The linearity tests reject the null for one and two location parameters (note that the null of this test corresponds to the ECM model estimated in table 3.7) and fails to reject it for three location parameters. In addition, the sequential tests for the parameters of the second location parameter in the auxiliary regression fail to reject the null, indicating that we need just one location parameter in the model. (Note that when $m = 1$ the sequential test is the same as the linearity test.)

The results of estimating the smooth transition panel ECM model are presented in table 3.9.

Table 3.8: Linearity and Location Selection Tests

Linearity Tests		
m	LM_χ	p-value
1	10.56	0.032
2	14.31	0.074
3	18.45	0.103
Sequential Tests		
m	LM_χ	p-value
1	10.56	0.032
2	4.872	0.301
3	10.21	0.037

The signs of the coefficients in the base regime are the same as the signs estimated for the standard panel ECM, and the magnitude of the coefficients is fairly close as well. As for the nonlinear part, we observe that as financial development goes up, the effect of income and wealth on consumption go down. Similarly, the effect of the interest rate on consumption also goes towards zero as financial development increases. The main result we get here is that, as financial development increases, the adjustment effect of consumption towards its long run equilibrium is stronger. This is evidenced by the fact that the coefficient of the error correction component ($z_{i,t-1}$) in the nonlinear part is of the same sign as the corresponding coefficient in the base regime (negative) and statistically significant.

Table 3.9: Smooth Transition Panel ECM Regression Results

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z_{i,t-1}$
Base Regime	0.222***	-0.458***	0.078***	-0.094***
	(0.048)	(0.131)	(0.013)	(0.032)
Nonlinear Part	-0.188**	0.598***	-0.058***	-0.087**
	(0.086)	(0.211)	(0.016)	(0.043)
ξ		95.24		
c		0.632		

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figures C.2 to C.5 in the Appendix show how the coefficients for each of the variables change as financial development goes up. These plots emphasize that the short-run effects shrink as financial development increases and that the adjustment towards the long-run relation gets stronger.

In table 3.10 we report the model evaluation tests for remaining heterogeneity coming from the financial development variable, and for parameter constancy across time. The null of both of these tests indicates that the model from table 3.9 is adequate when compared to the alternatives of a time varying version of it, or a model including an extra transition function related to financial development. In both cases we fail to reject the null, which suggests that the model is adequate.

Table 3.10: Model Evaluation Tests

	$LM\chi$	P-value
Parameter Constancy	6.036	0.643
Remaining Heterogeneity	11.51	0.175

3.6 Robustness Checks

In this section we present additional robustness checks of our model. The additional robustness checks concern including additional regressors in the model, modifying the long-run relation and using narrower measures of financial development. We also report on the sensitiveness of our results to the choice of starting values in the estimation procedure, on the impact of the international financial crisis, and on the difference between countries with a high level of financial development (alternatively income) and countries with a low level of financial development.

3.6.1 Additional Regressors

We begin by adding to the model variables that may plausibly have some impact on consumption in the short run. The variables we add to the model are the inflation rate, credit and the unemployment rate. Our data on credit is total credit to the private sector by banks and other financial institutions. This data comes from FRED for Austria, Belgium, Cyprus, Estonia, Finland, France, Greece, Germany, Ireland, Italy, Latvia, Lithuania, Luxembourg, Portugal, Slovakia, Slovenia, Spain, Sweden and Venezuela; from Bank for International Settlements (BIS) for Canada and New Zealand; and from the World Bank for all other countries. The data on the unemployment rate is from the ILOSTAT database provided by the International Labour Organization. We use data on the consumer price index obtained from the World Bank for all countries except Chile and Venezuela (for these two countries the data is from

FRED), to compute the inflation rate.

When we look at the regular panel ECM, adding the bew variables to the baseline model does not change much the coefficients of the variables which were already included in the model, in terms of either sign or magnitude—see table C.1. As for the coefficients of the variables which were added, inflation is not statistically significant in the model, having a negative sign, while credit has a positive and significant coefficient, and the unemployment rate has a negative and statistically significant coefficient.

In the smooth transition panel ECM, the new regressors also add very little to our original conclusions. The linearity tests are basically unchanged (cf. tables 3.8 and C.2), with the exception of the model including the unemployment rate. The estimation results—see tables C.3 and C.4—show that, in the base regime, none of the additional variables has statistical significance and, in the nonlinear part, the unemployment rate is not significant at the 10% level. Inflation has a positive sign in the nonlinear part, but the model evaluation tests for the model with inflation provide evidence against the model (table C.5). Credit has a positive and significant coefficient in the nonlinear part, and the model evaluation tests fail to reject the model as adequate, meaning that, as financial development goes up, credit has a larger short-run effect on consumption.

3.6.2 Long Run alternatives

There are other possibilities one might be willing to use in terms of long-run regressions for consumption, besides wealth and the interest rate. This means that we might consider other sets of variables in the cointegration tests and then in the estimation procedures. To see how different our results can be if we use other long-run regressions, we use the following as alternative long-run deviations:

$$\begin{aligned} z^a_{i,t} &= \log C_{i,t} - \theta_i - \alpha_1 \log W_{i,t} && (a) \\ z^b_{i,t} &= \log C_{i,t} - \theta_i - \alpha_1 \log Y_{i,t} - \alpha_2 r_{i,t} && (b) \\ z^c_{i,t} &= \log C_{i,t} - \theta_i - \alpha_1 \log Y_{i,t} && (c) \end{aligned} \tag{3.15}$$

Table C.6 presents the results of the cointegration tests for the variables involved in each of these new specifications of the long-run relation. For specification (a) the tests lean heavily towards cointegration among the variables, while for specification (b) the evidence pointing towards cointegration is slightly weaker, and in the case of specification (c) at the 5% level we fail to reject the absence of cointegration.

The results of the long-run regressions are reported in table C.7. The coefficients in the long-run regressions appear with the expected signs. Nevertheless, the interest rate does not have statistical significance in specification (b). The standard ECM estimation—table C.8—shows very similar coefficients for most variables when compared to the model in table 3.7. On the other hand, the error correction component has a lower coefficient in these alternative specifications and the statistical significance is weaker when income is substituted for wealth.

Next we present the results of the linearity and sequential homogeneity tests for these alternative models—see tables C.9 to C.11. Overall, the tests support the smooth transition model and suggest that we should use one location parameter in the specification. The results from these estimations—tables C.12 to C.14—are very close to our original model estimation in what concerns the short-run coefficients, both in the base regime and in the nonlinear part. The main difference, also seen in the traditional panel ECM, concerns the coefficient associated with the long-run component. This coefficient is only significant, in both the base regime and in the nonlinear part, when we use wealth in the cointegration relation (and not income). Finally, the model evaluation tests support the adequacy of these models—see table C.15.

3.6.3 Financial Development sub-indices

For most of our analysis we have been using a broad measure of financial development. This brings up the question of whether our results hold up once we consider only financial market development or financial institutions development. Our aim in this section is to analyze the robustness of our conclusions when we use one of the intermediate levels of the financial development index—recall section 2.4.

To this end we repeat the PSTR estimation procedure, but this time using either the financial institution development index (FI) or the financial market development index (FM) as the transition variable, instead of the financial development broad index. The results from these estimations are presented in appendix C.2.2.

The linearity test—table C.16—rejects the null of the linearity test for financial institution development. The results from the PSTR estimation using FI are very similar, in terms of both the signs and magnitudes of the coefficients, to the results from our original model—see table C.17. All the coefficients in the nonlinear part are statistically significant and the model is also validated by the model evaluation tests—table C.18.

As for financial market development, the linearity test has a p-value of 0.085—table C.19—and the results of the PSTR estimation—table C.20—seem much weaker than the ones from both the original model and the one using FI as transition variable. Now the only coefficients which are statistically significant in the nonlinear part are the ones concerning the interest rate and wealth. Despite this, the signs of the coefficients are still the same as in our original model and the model evaluation tests do not reject this model—table C.21.

What we conclude from this robustness analysis is that the effect of financial development on consumption appears to be largely driven by financial institutions development.

3.6.4 Other robustness tests

We now take into account the influence on our results of different starting values for the estimation procedure and the effect of the international financial crisis. We also check if our results are the same for countries with low and high levels of financial development and income.

- *Starting Values* - As the methodology is sensitive to the starting values of the parameters of the nonlinear part, we performed the estimations with different starting values. We found that, overall, the information we get from the estimates is essentially the same. That is to say, financial development promotes changes in the way consumption reacts to other variables and affects the speed of adjustment towards its long-run equilibrium;

- *Crisis years* - Our sample includes the period of the international financial crisis. To control for the effects of the crisis on our results, we do two things. The first is to redo our estimations without the observations from the start of the crisis (2007) onwards. When we do our results this are rather poor and do not reject the null of the linearity test. The second approach we take is to include in the short-run component of the model a dummy taking the value 1 since the start of the crisis. The dummy displays statistical significance. Nevertheless, the conclusions are pretty much the same as with our benchmark estimation concerning the result that financial development affects the short-run response. The result that financial development increases the speed of adjustment to long-term equilibrium is now weaker;

- *Sample Splitting* - Financial development might not have the same effect over consumption in countries with high financial development and in countries with low financial development. The same argument applies to income, as macroeconomic variables in countries with high income may behave differently from what is observed in countries with low income. To assess this possibilities we split the sample into groups of high and low financial development, and redid our estimations. Then we did the same using income as the criteria for splitting the sample. What we observe is that, after splitting the sample, the linearity test fails to reject the null in any of the groups, meaning that we do not observe the nonlinearity from which the PSTR specification originates.

3.7 Conclusion

Despite being unlikely that financial development exerts a direct effect over consumption levels, one can not rush into arguing that it does not cause any changes on consumption behavior whatsoever. In this chapter we explored the possibility that financial development induces changes in the way consumption responds to its typical determinants. To this end, inspired by the error correction model literature, we estimated a panel version of an ECM model applied to consumption and its determinants. We then used a Panel Smooth Transition Regression in order to observe possible changes in the coefficients of the model, both in terms of short-run responses of consumption to other variables and of consumption's adjustment towards long-run equilibrium.

Our results support the idea that the way consumption reacts to other variables changes with financial development, with the short-run coefficients of income, wealth and the interest rate getting closer to zero as financial development grows. On the other hand, as financial development increases, consumption adjusts faster towards its long-run equilibrium. Our robustness analysis also suggests that, despite the fact that we also find an effect coming from financial market development, the main results are driven by financial institution development.

The results we obtain are robust to most of the robustness checks we perform and overall they provide evidence that consumption behavior does react, at least in part, to changes in financial development. The fact that consumption's responses to other variables are different at different stages of financial development does advise caution when studying how one might stimulate it as overlooking this aspect might lead to effects that are different from the ones that were anticipated. A final note regarding the results from this chapter can be pointed regarding the estimated smoothness parameter. When the smoothness parameter in a panel smooth transition regression model is considerably larger than the other parameters in the model, the model itself starts to behave closely to what can be seen in a panel threshold model. Our results from this section, as reflected in fig. C.1 in part demonstrate this as a large part of the estimated values for the function are located in the extreme parts of it and not on the transition area itself. Following this tone, the next chapter takes a deeper look into the panel threshold regression models and their application to a consumption function.

Chapter 4

Threshold Effects of Financial Development on Consumption

4.1 Introduction

Consumption is one of the main macroeconomic aggregates of interest, and has been so for quite some time. With the passage of time, several empirical facts have challenged the standard theoretical framework on consumption, forcing it to adapt in order to better explain the intricacies of the real world. One of the modern challenges to consumption behavior modeling is taking into account the deep changes that the financial development process has brought with it.

The Permanent Income Hypothesis/Life-Cycle Theory stemming from the seminal works of Modigliani and Brumberg (1954) and Friedman (1957) was the driving force behind much of the research on consumption behavior. The theory gained an additional boost of popularity with the work of Hall (1978), due to the test it derives and the interpretations it can draw from the data. This advance was further complemented with a series of tests on the predictions and empirical evidence focusing on the excess sensitivity of consumption to income, as in Flavin (1981), Mankiw and Shapiro (1985) and Stock and West (1988).

With the bulk of the theory on consumption being supported by the theory of inter-temporal choice and optimization (Deaton, 1992), it feels natural that several of the modifications that have been proposed over time to deal with empirical regularities which disagree with the common theoretical predictions address precisely the aspects of the real world which imply that moving funds freely across time might not be possible. Credit plays a crucial role in the narrative of the permanent income hypothesis because it works as the prime way through which a consumer can consume today against her future wealth. The same can be said for the inter-temporal choice theory. In fact, credit provides the means for an impatient consumer to consume more today by using credit. But there is a trade-off: to consume more today, the consumer must consume less in the future, when the credit has to be repaid.

The fact that credit is obtained mainly through the financial system makes the discussion on financial development relevant to understanding consumption behavior. Financial development can have positive effects, such as reducing the intermediation costs, which by turn has a positive effect over consumption, as shown by Antunes et al. (2013). The debate on financial development first gained relevance in the consumption literature with the start of the de-regulation and financial liberalization processes in several major countries. Papers such as Blundell-Wignall et al. (1991), Girardin et al. (2000) and Bandiera et al. (2000) study how this process contributed to a decline in the share of population affected by liquidity constraints. The aftermath of the financial crisis also forced researchers to revisit the role some key variables play in modeling consumption behavior. Namely, wealth gained extra relevance in explaining consumption, as noted by Lee (2013), Fisher et al. (2012) and Estrada et al. (2014), and credit conditions were given an important role in explaining consumption shifts, as evidenced by Muellbauer (2007), Aron et al. (2012), Aron and Muellbauer (2013), Duca et al. (2011), Muellbauer and Murata (2009), Muellbauer and Williams (2012) and Guerrieri and Lorenzoni (2017).

Our objective in this chapter is to empirically analyze the impacts of financial development over consumption. To be specific, we assess not only the possibility of a direct effect of financial development on aggregate consumption, but also how different levels of financial development might change consumption's reaction to its more traditional explanatory variables.

Our chapter is related in terms of methodology to Beaton (2009), since we employ panel threshold regression to analyze changes in the behavior of the consumption function. Nevertheless, our analysis proceeds in a different way, given that we consider a panel dataset, we use financial development as the threshold variable instead of credit, and we allow all the regressors to be affected by the threshold effect. We apply the Panel Threshold Regression methodology of Hansen (1999) and the FD-GMM estimator of Seo and Shin (2016) to a panel dataset of 46 countries, with yearly observations from 2000 to 2014. We find evidence that financial development does induce regime changes in the behavior of aggregate consumption.

Our contributions within this chapter come from the application of Panel Threshold Regression to a wide dataset, with the goal of finding a link between a recent broad measure of financial development and aggregate consumption behavior. The usage of a recent technique to perform a Panel Threshold Regression, which accounts for the endogeneity of the regressors, is also a contribution of the chapter. The last contribution of our chapter is the comparison between the effect of financial development on consumption and the effect of credit.

The chapter is organized as follows. Section 4.2 describes the models we estimate, as well as the estimations procedures we use. Section 4.3 presents the data. Our results are reported in section 4.4. Section 4.5 analyses the models that use credit as the threshold variable. Section 4.6 concludes the chapter.

4.2 Model and Methodology

We study the impact of financial development on consumption in two ways. The first is to include financial development explicitly in the consumption model in order to test for a direct effect. The second is to consider non-linear models to account for the possibility of a more subtle effect, whereby financial development changes the behavior of consumption in response to shocks. This is done by applying a panel threshold regression to the consumption models, using financial development as the threshold variable.

4.2.1 Models

We start by estimating the following model:

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \epsilon_{i,t} \tag{4.1}$$

where C is consumption, Y is a measure of income, r is the real interest rate, W is a measure of wealth, ϵ is the error term, i identifies the country unit and t the time unit.

In order to test the hypothesis that financial development plays a role in explaining consumption we add a measure of financial development (FD) to our model:

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \alpha_4 \Delta \log FD_{i,t} + \epsilon_{i,t} \tag{4.2}$$

By doing this we are checking for a possible direct impact of financial development on consumption behavior. Additionally, we also add credit ($Cred$), as a control variable, to the previous specification:

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \alpha_4 \Delta \log FD_{i,t} + \theta \Delta Cred_{i,t} + \epsilon_{i,t} \tag{4.3}$$

There are two reasons why we introduce credit into our specification. First, because credit has been suggested in the literature as a possible regressor for consumption. Second, because our argument that the financial system is crucial for consumption smoothing makes the inclusion of credit a relevant issue. In other words, perhaps credit is a sufficient measure of financial development in the context of consumption behavior, and a broad measure of financial development is not necessary. We start with an Ordinary Least Squares (OLS) estimation of these models. Then, to take into account the possibility of endogeneity in these specifications, we also estimate them by means of instrumental variable (IV) estimators. Our choice of instruments follows those typically used in the literature (e.g., Jappelli and Pagano, 1989) and includes a linear trend, lagged government expenditure and lagged exports.

4.2.2 Threshold Methodology

To check for other effects of financial development on consumption we go further than adding it to the consumption function. It is plausible that the overall level of financial development of an economy may have an indirect impact on the consumption function by changing the response of it to its traditional explanatory variables. To detect this kind of effect we apply a threshold methodology, with the threshold variable being financial development. We expect to see noticeable differences between the coefficients across regimes.

We will use the methodology of Hansen (1999) to estimate a threshold regression model. Next we briefly describe the general procedure. Consider the model with two regimes:

$$y_{i,t} = \mu_i + \beta_1' x_{i,t} I(q_{i,t} \leq \gamma) + \beta_2' x_{i,t} I(q_{i,t} > \gamma) + e_{i,t} \tag{4.4}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, with N and T being the cross-sectional and the time dimensions, respectively. $x_{i,t}$ is a k-dimensional vector of regressors, $q_{i,t}$ is the threshold variable, μ_i represents fixed individual effects, $e_{i,t}$ is the error term and $I(\cdot)$ is the indicator function.

Alternatively we can write this model as:

$$y_{i,t} = \mu_i + \beta' x_{i,t}(\gamma) + e_{i,t} \tag{4.5}$$

with $\beta = (\beta_1', \beta_2')'$ and

$$x_{i,t}(\gamma) = \begin{bmatrix} x_{i,t} I(q_{i,t} \leq \gamma) \\ x_{i,t} I(q_{i,t} > \gamma \end{bmatrix} \tag{4.6}$$

To estimate this model, first we deal with the fixed effects by removing the individual specific means. This produces the transformed model:

$$y_{i,t}^* = \beta' x_{i,t}^*(\gamma) + e_{i,t}^* \tag{4.7}$$

where $y_{i,t}^* = y_{i,t} - \bar{y}_i$, $x_{i,t}^*(\gamma) = x_{i,t}(\gamma) - \bar{x}_i(\gamma)$ and $e_{i,t}^* = e_{i,t} - \bar{e}_i$. The bar identifies individual means. Note that:

$$\bar{x}_i(\gamma) = \frac{1}{T} \sum_{t=1}^{T} x_{i,t}(\gamma) = \begin{bmatrix} \frac{1}{T} \sum_{t=1}^{T} x_{i,t} I(q_{i,t} \leq \gamma) \\ \frac{1}{T} \sum_{t=1}^{T} x_{i,t} I(q_{i,t} > \gamma) \end{bmatrix}$$

We can write the model in matrix notation as:

$$Y^* = X^*(\gamma)\beta + e^* \tag{4.8}$$

Therefore, given value for γ, the vector of parameters β can be estimated by OLS:

$$\hat{\beta}(\gamma) = (X^*(\gamma)'X^*(\gamma))^{-1}X^*(\gamma)'Y^* \tag{4.9}$$

The next step is estimating γ. This parameter is chosen as to minimize the sum of squared errors:

$$S_1(\gamma) = \hat{e}^*(\gamma)'\hat{e}^*(\gamma) \tag{4.10}$$

with $\hat{e}^*(\gamma) = Y^* - X^*(\gamma)\hat{\beta}(\gamma)$. Estimation of β and γ can therefore be achieved by means of an iterative procedure.

An important issue that arises here is whether or not the data warrants the use of a threshold model instead of the simpler linear model. We can address this issue by testing for the existence of a threshold. The null hypothesis for the test is $H_0 : \beta_1 = \beta_2$. Under this null, the threshold parameter γ is not identified, which leads to a non-standard testing procedure. The testing procedure is to estimate γ as previously described, obtaining $S_1(\gamma)$, and then estimate the model under the null, which is:

$$y_{i,t} = \mu_i + \beta_1' x_{i,t} + e_{i,t} \tag{4.11}$$

This model is transformed by removing the individual specific means to get rid of the fixed effects. The transformed model is then estimated. Let S_0 denote the corresponding sum of squared errors. The likelihood ratio test statistic is then:

$$F_1 = \frac{(S_0 - S_1(\hat{\gamma}))}{\hat{\sigma}^2} \tag{4.12}$$

As the asymptotic distribution of F_1 is non-standard, a bootstrap procedure is used to obtain critical values and p-values.

4.2.3 Threshold Methodology with Endogenous Regressors: FD-GMM

One of the main drawbacks of the estimation methodology of section 4.2.2 is that it requires that the regressors (and the threshold variable) be exogenous. To go around this issue, Seo and Shin (2016) proposes a First Difference Generalized Method of Moments (FD-GMM). We use this methodology to address the possible endogeneity of the regressors in our model.

We now proceed to give a brief presentation of the FD-GMM estimation procedure based on both Seo and Shin (2016) and Seo et al. (2019). Start by considering the model:

$$y_{i,t} = \mu_i + (1, x'_{i,t})\beta_1 I(q_{i,t} \leq \gamma) + (1, x'_{i,t})\beta_2 I(q_{i,t} > \gamma) + e_{i,t} \tag{4.13}$$

where $x_{i,t}$ is the $k \times 1$ vector of regressors (which can include the lagged dependent variable), $I(\cdot)$ is the indicator function, $q_{i,t}$ is the threshold variable, γ is the threshold parameter, μ_i are the fixed effects and $e_{i,t}$ is the error term. Next consider the first difference transformation of this model, which yields:

$$\Delta y_{i,t} = \phi' \Delta x_{i,t} + \delta' X'_{i,t} \boldsymbol{I}_{i,t}(\gamma) + \Delta e_{i,t} \tag{4.14}$$

where $\phi = (\beta_{1,2}, \ldots, \beta_{1,k+1})'$ contains the coefficients associated with the base regime ($\beta_{1,j}$ are elements of β_1) and $\delta = \beta_2 - \beta_1$ shows the difference between the coefficients of both regimes. Note that

$$X_{i,t} = \begin{bmatrix} (1, x'_{i,t}) \\ (1, x'_{i,t-1}) \end{bmatrix} \quad \text{and} \quad \boldsymbol{I}_{i,t}(\gamma) = \begin{bmatrix} I(q_{i,t} > \gamma) \\ -I(q_{i,t-1} > \gamma) \end{bmatrix} \tag{4.15}$$

The objective is to estimate $\theta = (\phi', \delta', \gamma)'$. To avoid the bias generated by the correlation between the transformed regressors and the errors of the transformed model, the procedure requires a set of instruments $(z'_{i,t_0}, \ldots, z'_{i,T})'$, where $2 < t_0 < T$. The estimation method uses a Generalized Method of Moments (GMM, see Hansen, 1982) procedure based on the following sample moment condition:

$$\bar{g}_n(\theta) = \frac{1}{N} \sum_{i=1}^{N} g_{1i} - \frac{1}{N} \sum_{i=1}^{N} g_{2i}(\gamma)(\phi', \delta')' \tag{4.16}$$

where

$$g_{1i} = \begin{bmatrix} z_{i,t_0} \Delta y_{i,t_0} \\ \vdots \\ z_{i,T} \Delta y_{i,T} \end{bmatrix} \quad \text{and} \quad g_{2i}(\gamma) = \begin{bmatrix} z_{i,t_0}(\Delta x'_{i,t_0}, \boldsymbol{I}_{i,t_0}(\gamma)' X_{i,t_0}) \\ \vdots \\ z_{i,T}(\Delta x'_{i,T}, \boldsymbol{I}_{i,T}(\gamma)' X_{i,T}) \end{bmatrix} \tag{4.17}$$

The criterion function which is minimized in the GMM procedure is:

$$\bar{J}_n(\theta) = \bar{g}_n(\theta)' W_n \bar{g}_n(\theta) \tag{4.18}$$

W_n is the weight matrix. In the first step it is set to be:

$$W_n = \begin{pmatrix} \frac{2}{N}\sum_{i=1}^{N} z_{i,t_0} z'_{i,t_0} & \frac{-1}{N}\sum_{i=1}^{N} z_{i,t_0} z'_{i,t_0+1} & 0 & \cdots \\ \frac{-1}{N}\sum_{i=1}^{N} z_{i,t_0+1} z'_{i,t_0} & \frac{2}{N}\sum_{i=1}^{N} z_{i,t_0+1} z'_{i,t_0+1} & \ddots & \ddots \\ 0 & \ddots & \ddots & \frac{-1}{N}\sum_{i=1}^{N} z_{i,T-1} z'_{i,T} \\ \vdots & \ddots & \frac{-1}{N}\sum_{i=1}^{N} z_{i,T} z'_{i,T-1} & \frac{2}{N}\sum_{i=1}^{N} z_{i,T} z'_{i,T} \end{pmatrix}^{-1} \tag{4.19}$$

In the second step the weight matrix used is:

$$W_n = \left(\frac{1}{N} \sum_{i=1}^{N} \hat{g}_i \hat{g}_i' - \frac{1}{N^2} \sum_{i=1}^{N} \hat{g}_i \sum_{i=1}^{N} \hat{g}_i' \right)^{-1} \tag{4.20}$$

where $\hat{g}_i = (\Delta\hat{\epsilon}_{i,t_0} z'_{,it_0}, \ldots, \Delta\hat{\epsilon}_{i,T} z'_{i,T})'$ and $\Delta\hat{\epsilon}_{i,t}$ is the residual from the first step estimation. The criterion function is minimized in order to obtain a GMM estimate ($\hat{\theta}$) of the models' parameters.

As for the distribution of the parameters of the model, Seo and Shin (2016) show that it follows:

$$\begin{pmatrix} \sqrt{n} \begin{pmatrix} \hat{\phi} - \phi_0 \\ \hat{\delta} - \delta_n \end{pmatrix} \\ n^{1/2-\alpha}(\hat{\gamma} - \gamma_0) \end{pmatrix} \xrightarrow{d} \mathcal{N}\big(0, (G'\Omega^{-1}G)^{-1}\big) \tag{4.21}$$

where ϕ_0, δ_0 and γ_0 denote the true values of the parameters.

The estimated versions the asymptotic variance take $\hat{G} = (\hat{G}_\phi, \hat{G}_\delta(\gamma_0), \hat{G}_\gamma(\gamma_0))$, which is given by:

$$\hat{G}_\phi = \begin{bmatrix} \frac{-1}{N} \sum_{i=1}^{N} z_{i,t_0} \Delta x'_{i,t_o} \\ \vdots \\ \frac{-1}{N} \sum_{i=1}^{N} z_{,iT} \Delta x'_{i,T} \end{bmatrix} \tag{4.22}$$

$$\hat{G}_\delta(\gamma) = \begin{bmatrix} \frac{-1}{N} \sum_{i=1}^{N} z_{i,t_0} \boldsymbol{I}_{i,t_0}(\gamma)' X_{i,t_0}) \\ \vdots \\ \frac{-1}{N} \sum_{i=1}^{N} z_{i,T} \boldsymbol{I}_{i,T}(\gamma)' X_{i,T}) \end{bmatrix} \tag{4.23}$$

$$\hat{G}_\gamma(\theta) = \begin{bmatrix} \frac{1}{Nh} \sum_{i=1}^{N} z_{i,t_0} \Big[(1, x'_{i,t_0-1})' K(\frac{\gamma - q_{i,t_0-1}}{h}) - (1, x'_{i,t_0})' K(\frac{\gamma - q_{i,t_0}}{h}) \Big] \delta \\ \vdots \\ \frac{1}{Nh} \sum_{i=1}^{N} z_{i,T} \Big[(1, x'_{i,T-1})' K(\frac{\gamma - q_{i,T-1}}{h}) - (1, x'_{i,T})' K(\frac{\gamma - q_{i,T}}{h}) \Big] \delta \end{bmatrix} \tag{4.24}$$

where $K(\cdot)$ is a kernel function of choice for our estimations, in our case the Gaussian, and h is the bandwidth used for the kernel function, which in this case is Silverman's rule of thumb (see Silverman, 1986). We also obtain an estimate of Ω through:

$$\hat{\Omega}(\theta) = \frac{1}{N} \sum_{i=1}^{N} g_i(\theta) g_i(\theta)' - \frac{1}{N} \sum_{i=1}^{N} g_i(\theta) \frac{1}{N} \sum_{i=1}^{N} g_i(\theta)' \tag{4.25}$$

$$\text{with } g_i(\theta) = g_{1i} + g_{2i}(\theta)(\phi', \delta')'$$

A test for the existence of a threshold, a linearity test, is also derived for this model in Seo and Shin (2016). The null for this test is that the model is linear:

$$H_0 : \delta_0 = 0, \text{for any } \gamma \in \Gamma \tag{4.26}$$

The alternative is that $\delta_0 \neq 0$ for some $\gamma \in \Gamma$. The test used is a supremum type test:

$$\text{supW} = \sup_{\gamma \in \Gamma} \mathcal{W}_n(\gamma) \tag{4.27}$$

where $\mathcal{W}_n(\gamma)$ is the standard Wald statistic (see Wald, 1943, and Silvey, 1959) for each fixed γ:

$$\mathcal{W}_n(\gamma) = N\hat{\delta}(\gamma)'\hat{\Sigma}_\delta(\gamma)^{-1}\hat{\delta}(\gamma) \tag{4.28}$$

$\hat{\delta}(\gamma)$ is the GMM estimator of δ for a given γ and $\hat{\Sigma}_\delta$ is given by:

$$\begin{aligned} \hat{\Sigma}_\delta(\gamma) &= R\Big(\hat{V}_s(\gamma)'\hat{V}_s(\gamma)\Big)^{-1}R' \\ R &= (0_{(k+1)\times k}, I_{k+1}) \\ \hat{V}_s(\gamma) &= \hat{\Omega}\Big(\hat{\theta}(\gamma)\Big)^{-1/2}\Big(\hat{G}_\phi, \hat{G}_\delta\big(\hat{\theta}(\gamma)\big)\Big) \end{aligned} \tag{4.29}$$

The distribution of this test statistic is then obtained via bootstrap.

4.3 Data

Our dataset is a panel of yearly observations for 46 countries from 2000 to 2014. With the exception of credit, the series are the same as in the previous chapter. Nevertheless, for the sake of self-containedness of the chapter, we present all the information about the dataset in this section. Tables 4.1 to 4.5 report information about the coverage of the dataset, descriptive statistics and correlations.

The data for household consumption expenditures in constant 2010 prices in local currency was obtained from the National Accounts Main Aggregates Database (United Nations Statistics Division).

We retrieved the data for net disposable income in current local currency from AMECO for Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden, United Kingdom, Norway, Switzerland, United States, Japan, Canada, Mexico, South Korea, Australia, Bulgaria, Latvia, Lithuania, Poland, Czech Republic, Estonia, Hungary, Romania and Slovakia; from OECD for South Africa, New Zealand, Chile and Russia; and for all the other countries we obtained the data from UNdata (http://data.un.org/).

Data on the interbank interest rates was collected from FRED for South Africa, Russia, New Zealand, Norway, Mexico, Israel and Iceland; from the IMF's International Financial Statistics for Kuwait, South Korea, Thailand, Venezuela, Chile, Jamaica, Armenia, Australia, Canada and Switzerland; and from AMECO for all the other countries.

Table 4.1: List of countries

Armenia	Australia	Austria
Belgium	Bulgaria	Canada
Chile	Cyprus	Czech Republic
Denmark	Estonia	Finland
France	Germany	Greece
Hungary	Iceland	Ireland
Israel	Italy	Jamaica
Japan	Kuwait	Latvia
Lithuania	Luxembourg	Mexico
Netherlands	New Zealand	Norway
Poland	Portugal	Republic of Korea
Romania	Russian Federation	Slovakia
Slovenia	South Africa	Spain
Sweden	Switzerland	Thailand
Ukraine	United Kingdom	United States
Venezuela		

Table 4.2: Descriptive Statistics - levels

Variables	N	mean	sd	min	max
r	690	0.0404	0.0381	-0.0200	0.345
FD	690	0.583	0.230	0.0975	1
$Cred$	690	0.928	0.553	0.0568	3.121
$\log C$	690	30.31	1.681	26.76	34.64
$\log Y$	690	30.70	1.696	26.71	34.88
$\log W$	690	27.10	1.964	22.45	31.96

Table 4.3: Descriptive Statistics - differences

Variables	N	mean	sd	min	max
r	690	0.0404	0.0381	-0.0200	0.345
$\Delta \log C$	644	0.0260	0.0429	-0.191	0.178
$\Delta \log Y$	644	0.0259	0.0608	-0.386	0.302
$\Delta \log FD$	644	0.0104	0.0678	-0.272	0.288
$\Delta \log W$	644	0.0366	0.181	-0.813	0.581
$\Delta Cred$	644	0.0185	0.0932	-0.614	0.827

Table 4.4: Cross-correlation table

Variables	$\log C$	$\log Y$	r	$\log FD$	$\log W$	$Cred$
$\log C$	1.000					
$\log Y$	0.995	1.000				
r	-0.259	-0.273	1.000			
$\log FD$	0.555	0.573	-0.478	1.000		
$\log W$	0.957	0.961	-0.309	0.685	1.000	
$Cred$	0.347	0.342	-0.327	0.717	0.460	1.000

Table 4.5: Cross-correlation table

Variables	$\Delta \log C$	$\Delta \log Y$	r	$\Delta \log FD$	$\Delta \log W$	$\Delta Cred$
$\Delta \log C$	1.000					
$\Delta \log Y$	0.721	1.000				
r	0.179	0.122	1.000			
$\Delta \log FD$	0.286	0.102	0.082	1.000		
$\Delta \log W$	0.354	0.329	-0.149	0.255	1.000	
$\Delta Cred$	0.163	0.001	0.124	0.136	0.031	1.000

The data for each country's total wealth in current USD comes from Credit Suisse's Global Wealth Databooks.

Our data on credit concerns total credit to the private sector by banks and other financial institutions. The data comes from FRED for Austria, Belgium, Cyprus, Estonia, Finland, France, Greece, Germany, Ireland, Italy, Latvia, Lithuania, Luxembourg, Portugal, Slovakia, Slovenia, Spain, Sweden and Venezuela; from BIS for Canada and New Zealand; and from the World Bank for all other countries.

To obtain the real interest rate we employ the usual formula:

$$\text{real rate} = \frac{1 + \text{nominal rate}}{1 + \text{inflation rate}} - 1 \tag{4.30}$$

We use data on the consumer price index obtained from the World Bank for all countries except Chile and Venezuela (for which we resorted to FRED), to compute the inflation rate.

To obtain the net disposable income and total wealth in real terms, we calculated a consumption deflator using data on consumption expenditure in current prices and consumption expenditure at constant 2010 prices. To convert in USD we use the exchange rates from the National Accounts Main Aggregates Database.

As before, the main measure of financial development that we use is the broad-based index of financial development from Svirydzenka (2016). However, we will also employ the index of financial institution development, which is one of the intermediate indices used for computing the broad index. It incorporates measures of the depth, access and efficiency of financial institutions.

We will also use as instruments general government final consumption expenditures and exports of goods and services, both measured in USD at 2010 prices. The data was collected from the National Accounts Main Aggregates Database.

4.4 Results

In this section we present the results from our estimations. We report robust standard errors of the Huber (1967)/White (1980, 1982) type, modified to allow for within-group serial correlation. The standard errors for the estimates obtained by the FD-GMM procedure that allows for endogenous regressors in the threshold model were computed using the distributions described in section 4.2.3.

The results are obtained using the resources available from the *xtreg* command, the *xthreg* command (Wang, 2015) and the *xthenreg* command (Seo et al., 2019), all for Stata (StataCorp, 2017).

4.4.1 Baseline Models, Fixed Effects

We start by reporting the results for our initial, linear, models in eqs. (4.1) to (4.3). We estimate these models by fixed effects and the estimates are shown in table 4.6.

The signs of the estimated coefficients for GDP, wealth and credit are in line with what one would expect, i.e., they are positive. Regarding financial development, we observe that it has a positive and statistically significant coefficient, indicating that it might have a direct positive effect over consumption.

4.4.2 Baseline Models, Instrumental Variables

We now account for the possible endogeneity arising from disposable income. The instruments we use are lagged log exports, lagged log government consumption expenditures and a linear trend. The estimates are reported in table 4.7.

There are a few differences in the results of the IV estimations when compared to the OLS estimates. The main differences are the noticeably larger coefficient on disposable income

Table 4.6: Fixed Effects Estimation

	(1)	(2)	(3)
Δ log Y	0.424***	0.43***	0.433***
	(0.069)	(0.061)	(0.059)
r	0.077	0.08	0.046
	(0.075)	(0.076)	(0.079)
Δ log W	0.045***	0.034***	0.034***
	(0.009)	(0.007)	(0.008)
Δ log FD		0.09**	0.079**
		(0.036)	(0.034)
Δ Cred			0.058***
			(0.017)
R^2	0.5204	0.5409	0.5584

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and the loss of statistical significance of the wealth coefficient. Nevertheless, the signs of the coefficients remain the same and the effect of financial development remains positive and statistically significant, emphasizing the possible direct effect over consumption.

4.4.3 Threshold Estimation - Without endogeneity

This section focuses on the estimation of a threshold static model of consumption, without accounting for possible endogeneity of the regressors. To this end we estimate versions of eqs. (4.1) to (4.3) using the Hansen (1999) threshold methodology. As an illustration, note that, in the case of the model given by eq. (4.3), the threshold version corresponds to the following equation:

$$\begin{aligned}\Delta \log C_{i,t} = \mu_i + I(FD_{i,t} \leq c)\Big[\alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \\ + \alpha_4 \Delta \log FD_{i,t} + \theta \Delta Cred_{i,t}\Big] + I(FD_{i,t} > c)\Big[\alpha_1^* \Delta \log Y_{i,t} + \alpha_2^* r_{i,t} + \\ + \alpha_3^* \Delta \log W_{i,t} + \alpha_4^* \Delta \log FD_{i,t} + \theta^* \Delta Cred_{i,t}\Big] + \epsilon_{i,t} \quad (4.31)\end{aligned}$$

where $I(\cdot)$ is the indicator function and c is the threshold parameter.

The threshold versions, such as the model in the above equation, include one threshold, meaning that we allow for two regimes in consumption behavior. The threshold model allows us to observe possible non-linear effects of financial development on consumption by making

Table 4.7: Fixed Effects IV Estimation

	(1iv)	(2iv)	(3iv)
Δ log Y	0.609***	0.585***	0.611***
	(0.11)	(0.104)	(0.106)
r	0.058	0.063	0.025
	(0.06)	(0.066)	(0.069)
Δ log W	0.023*	0.015	0.012
	(0.014)	(0.013)	(0.014)
Δ log FD		0.098**	0.088**
		(0.045)	(0.044)
Δ Cred			0.061***
			(0.022)
R^2	0.4551	0.4948	0.4982

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the coefficients of the estimated consumption function change (discretely) when financial development passes a threshold. Passing the threshold induces a regime change in consumption behavior. The first step then is to perform the test for the existence of a threshold. The null hypothesis is that there is no threshold, i.e., that the linear model is adequate—recall section 4.2.2. The results of this test, for each of the three models in eqs. (4.1) to (4.3), are in table 4.8.

Table 4.8: Threshold test

	(1)	(2)	(3)
F_1	74.95	75.77	100.63
P-value	0.0010	0.0020	0.0010

All the tests indicate a strong rejection of the null hypothesis, meaning that there is evidence in favor of the existence of a threshold related to financial development. The estimates of the threshold models are presented in tables 4.9 and 4.10. The results support the hypothesis that financial development does shift consumption behavior. The estimated threshold is in the 0.35–0.4 band, a reasonable value for it considering one expects the benefits of financial development to come from a moderate amount of it.

The difference in the coefficients between regimes is quite sharp. The coefficients of GDP, wealth and credit go down in the second regime—the regime with higher levels of financial development—implying that these variables have a smaller impact on consumption dynamics in more financially developed countries. The coefficients of the interest rate and financial development are higher in the second regime and also become statistically significant. As for the signs of the coefficients, once more, the results are what one would expect.

Overall, the results from this section indicate that there may be a direct effect of financial development on consumption behavior. Furthermore, the direct effect of financial development and of the other variables on consumption may depend on the level of financial development itself.

Table 4.9: Threshold - base regime estimates

	(1t)	(2t)	(3t)
Δ log Y	0.52***	0.53***	0.504***
	(0.089)	(0.084)	(0.066)
r	-0.015	-0.015	-0.021
	(0.075)	(0.079)	(0.087)
Δ log W	0.064***	0.051**	0.074***
	(0.015)	(0.019)	(0.016)
Δ log FD		0.098*	0.032
		(0.053)	(0.05)
Δ Cred			0.228***
			(0.06)
Threshold	0.3849	0.3818	0.3995
R^2	0.5714	0.5902	0.6192

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.4 Threshold Estimation - With endogeneity

We now use the methodology of Seo and Shin (2016), described in section 4.2.3. The question of interest is still whether there are regime changes in consumption behavior induced by financial development crossing a certain threshold. As before, we are estimating threshold versions—equation 4.13—of the models given by equations 4.1, 4.2 and 4.3. The threshold model corresponding to equation 4.3, for example, can be written as:

$$\Delta \log C_{i,t} = \mu_i + (1, \Delta \log Y_{i,t}, r_{i,t}, \Delta \log W_{i,t}, \Delta \log FD_{i,t}, \Delta Cred_{i,t})\beta_1 I(FD_{i,t} \leq \gamma) + \\ +(1, \Delta \log Y_{i,t}, r_{i,t}, \Delta \log W_{i,t}, \Delta \log FD_{i,t}, \Delta Cred_{i,t})\beta_2 I(FD_{i,t} > \gamma) + e_{i,t} \quad (4.32)$$

Table 4.10: Threshold - second regime estimates

	(1t)	(2t)	(3t)
Δ log Y	0.323***	0.328***	0.332***
	(0.052)	(0.045)	(0.046)
r	0.39***	0.379***	0.329***
	(0.089)	(0.079)	(0.083)
Δ log W	0.029***	0.022***	0.017**
	(0.009)	(0.008)	(0.007)
Δ log FD		0.082**	0.078**
		(0.034)	(0.035)
Δ Cred			0.032***
			(0.009)

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

where β_1 and β_2 are vectors of parameters. After the first-difference transformation (recall equation 4.14), the model becomes:

$$\Delta^2 \log C_{i,t} = \phi_Y \Delta^2 \log Y_{i,t} + \phi_r \Delta_r r_{i,t} + \phi_W \Delta^2 \log W_{i,t} + \\ +\phi_{FD} \Delta^2 \log FD_{i,t} + \phi_{Cred} \Delta^2 Cred_{i,t} + \delta' X'_{i,t} \boldsymbol{I}_{i,t}(\gamma) + \Delta e_{i,t} \tag{4.33}$$

where

$$X_{i,t} = \begin{bmatrix} (1, \Delta \log Y_{i,t}, r_{i,t}, \Delta \log W_{i,t}, \Delta \log FD_{i,t}, \Delta Cred_{i,t}) \\ (1, \Delta \log Y_{i,t-1}, r_{i,t-1}, \Delta \log W_{i,t-1}, \Delta \log FD_{i,t-1}, \Delta Cred_{i,t-1}) \end{bmatrix} \\ \boldsymbol{I}_{i,t}(\gamma) = \begin{bmatrix} I(FD_{i,t} > \gamma) \\ -I(FD_{i,t-1} > \gamma) \end{bmatrix} \tag{4.34}$$

The results from the estimation of equation 4.33 are presented in tables 4.11 and 4.12. In the base regime, both GDP and wealth appear with the typical positive and significant coefficient. The interest rate either appears without statistical significance or with a negative and significant coefficient. Credit appears with positive and significant coefficient.

As for the differences between the coefficients in the two regimes, the first thing we notice is that the differences are statistically significant. Income and wealth have negative and significant estimated coefficients for the differences between regimes, with wealth's difference being very close to the coefficient for the base regime. The interest rate has a positive and significant difference coefficients in the models where it had negative and significant base regime coefficients (the models corresponding to equations 4.2 and 4.3). Credit has a negative difference coefficient.

Financial development appears in the base regime as having a negative coefficient in all models in which it is included. However, it is only significant in one of these models, while the difference coefficient for financial development is positive and statistically significant in all models in which the variable is included.

The estimates obtained with the FD-GMM estimator, which take the possibility of endogeneity into account, do show some differences relative to the estimates obtained assuming exogeneity, reported in the previous subsection. Aside from the magnitudes of some coefficients, the most noticeable difference is the fact the interest rate is now significant in some cases in the base regime. Overall, the results in this section suggest that financial development has a nonlinear direct impact on consumption. This impact is stronger in financially developed countries. Financial development also has an indirect effect through the threshold. Thus, financial development impacts the way in which consumption reacts to its more traditional determinants. Among these, income and wealth are much less important in explaining consumption dynamics in financially developed countries.

As an additional exercise, we also performed some robustness checks regarding the impact of the crisis on our results as well as using the income level as the threshold variable. These robustness checks add very little to our main results and thus are not reported.

Table 4.11: Endogenous Threshold - base regime estimates

	(1et)	(2et)	(3et)
ϕ_Y	0.813***	0.617***	0.655***
	(0.035)	(0.024)	(0.038)
ϕ_r	0.009	-0.067*	-0.184***
	(0.019)	(0.038)	(0.051)
ϕ_W	0.087***	0.133***	0.111***
	(0.011)	(0.022)	(0.02)
ϕ_{FD}		-0.047**	-0.027
		(0.018)	(0.027)
ϕ_{Cred}			0.513***
			(0.078)
Threshold	0.347	0.347	0.352
$p$value	0.00	0.00	0.00

standard errors in parentheses

pvalue refers to the pvalue from the linearity test

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Endogenous Threshold - regime differences

	(1et)	(2et)	(3et)
δ_Y	-0.411***	-0.156***	-0.204***
	(0.028)	(0.021)	(0.034)
δ_r	0.079	0.217***	0.544***
	(0.055)	(0.075)	(0.097)
δ_W	-0.088***	-0.155***	-0.119***
	(0.012)	(0.018)	(0.019)
δ_{FD}		0.112***	0.085**
		(0.02)	(0.034)
δ_{Cred}			-0.549***
			(0.08)

standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5 Credit, Institutions and Financial Development

The literature has studied how credit affects consumption—see for instance Ludvigson (1999); Aron et al. (2012); Buera and Moll (2015) and Kichian and Mihic (2018). A large fraction of this literature finds that credit has a positive impact over consumption, which is in line with our results from the previous section. Another question that might be asked is: How does credit change the response of consumption to the other regressors? A variant of this question has been asked in papers such as Bacchetta and Gerlach (1997) and Sarno and Taylor (1998). In those papers it is observed that consumption's excess sensitivity to income tends to decline with the financial deregulation process and the lifting of credit constraints. Some examples in the literature which are closely linked to the analysis we do here are Beaton (2009) and Cho and Rhee (2017). In Beaton (2009) credit is considered as the threshold variable for the aggregate consumption function. Cho and Rhee (2017) use household debt as a transition variable to study how the coefficients of their consumption model change with the level of credit. These approaches, like ours, base themselves on the idea that consumption smoothing is being held back by constraints on the movement of resources through time. In the previous sections we found evidence that financial development has some effect on consumption behavior, which we believe to be linked with the foregoing argument.

One may also ask whether this effect is limited to credit, in which case accounting for credit alone would suffice to capture the effect of financial development over consumption. Alternatively, is there some other effect at work that produces the observed effect of financial development on aggregate consumption? In this section we investigate where the effect might be coming from, be it credit alone, financial institution development or financial development in a broad sense. Our approach to this is to redo the analysis from the previous sections replacing the threshold variable—the broad financial development index—with credit and financial institution development. As we will see, the results in this section indicate that we can find a threshold effect in all three cases. However, the model where credit is isolated appears to be weaker, and the model with financial institution development seemingly associates the second regime to a higher level of financial development than the model with financial development itself.

4.5.1 Credit as a Threshold Variable

In this section we focus on the basic model from equation 4.1 and consider a modified version of equation 4.2 where we use credit instead of the broad financial development index. Additionally, we also use credit as the threshold variable. Thus, the models on which we base our analysis in this section are:

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \epsilon_{i,t} \tag{4.1}$$

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \alpha_4 \Delta Cred_{i,t} + \epsilon_{i,t} \tag{4.35}$$

The results from estimating these linear models, both using OLS and IV, are presented in table 4.13. Credit appears with a positive and significant coefficient in the models in which it was included.

Next we apply the panel threshold regression methodology to these two models, using credit as the threshold variable. The results are presented in tables 4.14 and 4.15. Looking at the p-values, the evidence in favor of the existence of a threshold in credit for these two models is not as clear as it was when we used financial development as the threshold variable, but it is still strong. In fact, the results are not very different from the results in the previous sections. The coefficients of income and wealth are smaller in the second regime, as is the case for credit. The coefficient of the interest rate is bigger in the second regime than in the first. The most noticeable difference between the models is that now wealth is barely statistically significant in the second regime.

As for the FD-GMM procedure for estimating a panel threshold model with endogenous regressors, the results are shown in tables 4.16 and 4.17. The null of the linearity test is rejected and the results for the base regime in these estimations are not very different from those in the previous sections. The main dissimilarities can be seen in the differences between

Table 4.13: Credit Models - Fixed Effects Estimation and IV estimation

	(1)	(35)	(1iv)	(35iv)
Δ log Y	0.424***	0.428***	0.609***	0.639***
	(0.069)	(0.065)	(0.11)	(0.113)
r	0.077	0.04	0.058	0.015
	(0.075)	(0.078)	(0.06)	(0.065)
Δ log W	0.045***	0.043***	0.023*	0.018
	(0.009)	(0.009)	(0.014)	(0.014)
Δ Cred		0.066***		0.07**
		(0.02)		(0.027)
R^2	0.5204	0.5431	0.4551	0.4580

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

coefficients across regimes: in the model with credit, income is estimated to have a higher effect on consumption in the second regime.

To summarize, using credit as a threshold variable leads basically to the same conclusions that we obtained previously with a general measure of financial development. This suggests that most of the effect of financial development on consumption might actually be coming from the credit channel. Our results in this section are in line with the literature in the sense that higher credit tends to reduce the excess sensitivity of consumption.

4.5.2 Financial Institution Development as a Threshold Variable

In this subsection we follow the same procedure as in above, but this time we use the index of financial institution development—see section 2.4—as the measure of financial development. The reference models are still those in equations 4.1, 4.2 and 4.3. The later two are modified to include financial institution development instead of broad financial development. To be specific, this means we will be turning our attention to the models:

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \epsilon_{i,t} \tag{4.1}$$

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \alpha_4 \Delta \log FI_{i,t} + \epsilon_{i,t} \tag{4.36}$$

Table 4.14: Credit Threshold - base regime estimates

	(1-thcred)	(35-thcred)
Δ log Y	0.432***	0.437***
	(0.094)	(0.073)
r	0.036	0.007
	(0.076)	(0.084)
Δ log W	0.061***	0.067***
	(0.014)	(0.013)
Δ Cred		0.202***
		(0.05)
Threshold	1.0283	0.9064
$p$value	0.055	0.006
R^2	0.5419	0.5827

robust standard errors in parentheses

pvalue refers to the pvalue from the linearity test

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

$$\Delta \log C_{i,t} = \mu_i + \alpha_1 \Delta \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \Delta \log W_{i,t} + \alpha_4 \Delta \log FI_{i,t} + \theta \Delta Cred_{i,t} + \epsilon_{i,t} \tag{4.37}$$

where FI is the index of financial institution development.

The results of the various estimations can be found in tables 4.18 to 4.22.

The linear models once more add very little to the discussion, with the coefficients of the traditional regressors having the usual signs. Financial institution development appears with a positive and significant sign in all models except the model with credit when it is estimated by IV. The coefficient for credit is positive and significant in the models where the variable is included.

Regarding the threshold models, the most noticeable difference we observe here in comparison with the benchmark model is the value of the threshold itself. Both the broad financial development index and the financial institution development index range from zero to one, but while the threshold is near 0.4 when using broad financial development, now the threshold parameter is estimated to be much higher, near 0.6 and above. This indicates that for financial institution development to induce a regime change in consumption it requires a substantially larger level than in the case of general financial development. The second noticeable difference we observe in comparison with the benchmark model is that wealth

Table 4.15: Credit Threshold - second regime estimates

	(1-thcred)	(35-thcred)
Δ log Y	0.344***	0.385***
	(0.062)	(0.071)
r	0.37***	0.22*
	(0.087)	(0.131)
Δ log W	0.018	0.018*
	(0.011)	(0.009)
Δ Cred		0.031**
		(0.012)

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and financial institution development lose statistical significance in the second regime of the threshold model estimated assuming exogeneity. The rest of the results are rather close to what we found in the previous sections.

4.6 Conclusion

The analysis of consumption behavior has come a long way since the dawn of the Rational Expectations Permanent Income Hypothesis/Life Cycle Theory. Several modifications and extensions have been considered to accommodate the empirical evidence that was accumulated over the years, as well as the impact of the ever-changing economic environment. One of the main changes of the past few decades in most countries was the development of the financial system.

In order to study the effects of financial development on consumption, we use include a proxy for financial development—the broad financial development index of Svirydzenka (2016)—in the model for consumption. Aside from this direct effect, we also employ non-linear models—estimated by the panel threshold regression of Hansen (1999) and the FD-GMM panel threshold methodology allowing for endogenous regressors of Seo and Shin (2016)—to incorporate the possibility of indirect effects of financial development on consumption. Namely, we are interested in the changes financial development induces in the response of consumption to its more traditional explanatory variables.

The results we obtain largely support the non-linear indirect effect of financial development on the consumption function. The evidence in favor of the explicit direct effect is not as

Table 4.16: Credit Endogenous Threshold - base regime estimates

	(1-ethcred)	(35-ethcred)
ϕ_Y	0.503***	0.183***
	(0.038)	(0.023)
ϕ_r	-0.167***	-0.38***
	(0.04)	(0.049)
ϕ_W	0.141***	0.135***
	(0.021)	(0.015)
ϕ_{Cred}		0.519***
		(0.061)
Threshold	0.478	0.698
$p$value	0.00	0.00

standard errors in parentheses

pvalue refers to the pvalue from the linearity test

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

strong. On balance, our results suggest that in our sample financial development does change consumption behavior, in the sense that it changes the way consumption reacts to its determinants. In addition, this effect is very likely due to the effect that the availability of credit has on consumption. Our results support the vast literature on the effects of financial sector development on consumption, and consequently on the real sector of the economy.

Table 4.17: Credit Endogenous Threshold - regime differences

	(1-ethcred)	(35-ethcred)
δ_Y	-0.079***	0.28***
	(0.028)	(0.039)
δ_r	0.517***	0.87***
	(0.045)	(0.105)
δ_W	-0.167***	-0.156***
	(0.021)	(0.018)
δ_{Cred}		-0.5***
		(0.064)

standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.18: Financial Institutions Development Models - Fixed Effects Estimation and IV estimation

	(1)	(36)	(37)	(1iv)	(36iv)	(37iv)
Δ log Y	0.424***	0.421***	0.425***	0.609***	0.592***	0.625***
	(0.069)	(0.066)	(0.063)	(0.11)	(0.109)	(0.113)
r	0.077	0.062	0.03	0.058	0.046	0.009
	(0.075)	(0.076)	(0.078)	(0.06)	(0.062)	(0.066)
Δ log W	0.045***	0.041***	0.04***	0.023*	0.022	0.018
	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)	(0.015)
Δ log FI		0.075***	0.058**		0.065**	0.045
		(0.025)	(0.023)		(0.029)	(0.027)
Δ Cred			0.061***			0.067***
			(0.018)			(0.026)
R^2	0.5204	0.5286	0.5479	0.4551	0.4723	0.4716

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.19: Financial Institutions Threshold - base regime estimates

	(1-thfi)	(36-thfi)	(37-thfi)
Δ log Y	0.446***	0.442***	0.453***
	(0.096)	(0.092)	(0.074)
r	0.032	0.012	-0.012
	(0.076)	(0.077)	(0.083)
Δ log W	0.062***	0.059***	0.071***
	(0.014)	(0.013)	(0.014)
Δ log FI		0.013**	0.039
		(0.033)	(0.03)
Δ Cred			0.202***
			(0.058)
Threshold	0.6687	0.6687	0.6378
$p$value	0.045	0.027	0.0000
R^2	0.55	0.5597	0.6012

robust standard errors in parentheses

pvalue refers to the pvalue from the linearity test

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.20: Financial Institutions Development Threshold - second regime estimates

	(1-thfi)	(36-thfi)	(37-thfi)
Δ log Y	0.301***	0.297***	0.325***
	(0.057)	(0.055)	(0.057)
r	0.376***	0.363***	0.299***
	(0.098)	(0.101)	(0.089)
Δ log W	0.019	0.015	0.012
	(0.012)	(0.011)	(0.009)
Δ log FI		0.053	0.05
		(0.036)	(0.033)
Δ Cred			0.032***
			(0.01)

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.21: Financial Institutions Development Endogenous Threshold - base regime estimates

	(1-ethfi)	(36-ethfi)	(37-ethfi)
ϕ_Y	0.608***	0.614***	0.503***
	(0.024)	(0.049)	(0.041)
ϕ_r	0.209***	-0.171***	-0.132
	(0.033)	(0.058)	(0.114)
ϕ_W	0.0329***	0.004	0.066***
	(0.005)	(0.005)	(0.015)
ϕ_{FI}		0.196***	-0.0003
		(0.027)	(0.056)
ϕ_{Cred}			0.102*
			(0.06)
Threshold	0.77	0.843	0.561
$p$value	0.00	0.00	0.00

standard errors in parentheses

pvalue refers to the pvalue from the linearity test

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.22: Financial Institutions Development Endogenous Threshold - regime differences

	(1-ethfi)	(36-ethfi)	(37-ethfi)
δ_Y	-0.303***	-0.443***	-0.196***
	(0.063)	(0.13)	(0.057)
δ_r	0.012	2.037***	1.057***
	(0.059)	(0.3)	(0.118)
δ_W	-0.029***	-0.072***	-0.103***
	(0.009)	(0.021)	(0.014)
δ_{FI}		0.671***	0.523***
		(0.229)	(0.085)
δ_{Cred}			-0.146**
			(0.062)

standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Nonparametric Analysis of Financial Development and Consumption

5.1 Introduction

The structure of the economies and the way they work has changed markedly over the last decades. One of the major changes of the past decades has been the unprecedented level of financial development achieved. This development leads to the question of whether and how what happens in the financial system affects the rest of the economy. In particular, given the importance of consumption smoothing across time in standard models, consumption is a natural focus for research on the wider effects of financial development. In fact, as Deaton (1992) stresses, most of the models of consumption assumed that it is possible to smooth consumption over several time periods. This implies that there is some form of a financial system in operation. Changes to that financial system that expand or restrict the ability to smooth consumption may therefore affect consumption. This is the primary reason for posing the hypothesis that financial development may impact consumption. The model in Guerrieri and Lorenzoni (2017) shows that a recession originated in the financial system can impact consumption, as well as the interest rate and output, through a credit crunch. Other examples of authors that show how consumption might possibly be linked with changes to the financial system can be found in Bandiera et al. (2000), Carvalho et al. (2012), Martin and Ventura (2011), Dewachter and Wouters (2014) and He and Krishnamurthy (2014).

Related to the previous argument is the possibility that financial development may have not just a direct impact on consumption, but also an indirect effect. The indirect impact would consist of a change in the way consumption responds to its other, traditional, determinants. This has been studied in, e.g., Lee (2013), Fisher et al. (2012) and Estrada et al. (2014).

In this chapter we use nonparametric methods to estimate a consumption model and analyze whether and how consumption reacts to financial development. The nonparametric approach has two advantages over a parametric model. First, it allows us to form an idea of what the link between consumption and financial development might look like without imposing strong a priori assumptions about it. Second, it allows us to dodge most of the discussion on what form should the consumption function take, i.e., how should the traditional variables enter it. Despite these advantages, applications of nonparametric methodologies to the analysis of aggregate consumption analysis are relatively scarce. Notable exceptions are Swofford and Whitney (1987), Delgado and Miles (1997), Easaw et al. (2005), Cherchye et al. (2007), Cherchye et al. (2009) and Bruno (2014).

The results we obtain show some evidence of a nonlinear effect of financial development on consumption, with the effect depending on the value of the remaining regressors as well. The effect is negative for low values of the remaining regressors and positive for high values of the remaining regressors.

The chapter is organized as follows. Section 5.2 introduces both the parametric and the non-parametric models used in the study. Section 5.3 describes the nonparametric techniques that we used to estimate the models. Section 5.4 provides a brief presentation of our data. Section 5.5 reports the results of the parametric model and section 5.6 does the same for the nonparametric regression models. Section 5.7 concludes the chapter.

5.2 Model

In this section we present the consumption models that we will use throughout the chapter to study consumption behavior and its relation to financial development. Regarding notation, despite the fact that we use panel data, in this section and in section 5.3 we present the formulas concerning the nonparametric models and techniques as if we were using cross-sectional data, i.e., we omit the time subscript. This is related to the way in which we deal with the fixed effects, which is by including a discrete variable $Country$ in the equations. We believe that this change of notation improves the readability of the equations.

5.2.1 Parametric Model - Benchmark

Our benchmark parametric model with fixed effects is:

$$\log C_{i,t} = \mu_i + \alpha_0 \log C_{i,t-1} + \alpha_1 \log Y_{i,t} + \alpha_2 r_{i,t} + \alpha_3 \log W_{i,t} + \alpha_4 FD_{i,t} + u_{i,t} \quad (5.1)$$

where C is a measure of consumption, Y is a measure of current income, r is the real interest rate, W is a measure of current wealth and FD is a measure of the level of financial development.

We use a country fixed-effects estimation of the model in equation 5.1 as benchmark for our nonparametric models. The notation assumes that the panel dataset includes n cross-section units, with T time observations each, corresponding to a sample of nT observations.

5.2.2 Nonparametric Model

The model of interest is the nonparametric version of equation 5.1. To be specific, we will be estimating the following model for consumption:

$$\log C_i = g(\boldsymbol{x}_i) + u_i \tag{5.2}$$

where $g(\cdot)$ is an unknown smooth function which we wish to estimate, $\boldsymbol{x}_i$ is a vector including the regressors from equation 5.1, and u_i is the error term.

We control for fixed effects by including a discrete unordered variable $Country$, which identifies the country to which the observation belongs. This is very similar to the dummy approach in the parametric setting. In the parametric case, allowing for fixed effects is tantamount to including individual dummies in the model. In the nonparametric case, one variable with a different value for each country (e.g., 1 for the first country, 2 for the second country, and so forth) is enough to control for these fixed effects. Thus, the nonparametric model allowing for fixed effects is:

$$\log C_i = g(\boldsymbol{x}_i, Country_i) + u_i \tag{5.3}$$

5.3 Methodology

Our description of the methodologies used here draw heavily on the presentations provided by Li and Racine (2007) and Henderson and Parmeter (2015). As we present the methodology, we use the model in equation 5.2 to illustrate the procedures.

5.3.1 Nonparametric Regression - Local Linear Least Squares

The logic behind the Local Linear Least Squares (LLLS) method is that we are minimizing the weighted squared distance between the dependent variable and a local linear approximation to the unknown function $g(\cdot)$ we wish to estimate. Taking our equation 5.2 as an example, expanding the function $g(\boldsymbol{x}_i)$ around $\boldsymbol{x}$ would give:

$$\begin{aligned} \log C_i &= g(\boldsymbol{x}_i) + u_i \\ &\approx g(\boldsymbol{x}) + (\boldsymbol{x}_i - \boldsymbol{x})\beta(\boldsymbol{x}) + u_i \end{aligned} \tag{5.4}$$

where $\beta(\boldsymbol{x})$ is the gradient vector of length q at point $\boldsymbol{x}$. From here we move on to the minimization problem:

$$\min_{g(\boldsymbol{x}),\beta(\boldsymbol{x})} \sum_{i=1}^{nT} \big[\log C_i - g(\boldsymbol{x}) - (\boldsymbol{x}_i - \boldsymbol{x})\beta(\boldsymbol{x})\big]^2 K_h(\boldsymbol{x}_i, \boldsymbol{x}) \tag{5.5}$$

where $K_h(\boldsymbol{x_i}, \boldsymbol{x})$ is a product-kernel weighting function. The product-kernel function takes the form:

$$K_h(\boldsymbol{x}_i, \boldsymbol{x}) = \prod_{d=1}^{q} k\Big(\frac{x_{i,d} - x_d}{h_d}\Big) \tag{5.6}$$

with k being the univariate kernel chosen to smooth each of the regressors, and the index d identifying the regressor in the model.

The solution, $\hat{\delta}(\boldsymbol{x})$, to this minimization problem can be written in matrix notation as:

$$\hat{\delta}(\boldsymbol{x}) = \begin{bmatrix} \hat{g}(\boldsymbol{x}) \\ \hat{\beta}(\boldsymbol{x}) \end{bmatrix} = \big[\boldsymbol{X}' K(\boldsymbol{x}) \boldsymbol{X}\big]^{-1} \boldsymbol{X}' K(\boldsymbol{x}) \log \boldsymbol{C} \tag{5.7}$$

In the above equation, $\log \boldsymbol{C}$ is the $nT \times 1$ vector of observations of the dependent variable, $\boldsymbol{X}$ is a $nT \times (q+1)$ matrix with the ith row given by $\boldsymbol{X}_i = [1, (\boldsymbol{x}_i - \boldsymbol{x})]$ and $K(\boldsymbol{x})$ a $nT \times nT$ diagonal matrix with the kernel functions $K_h(\boldsymbol{x}_i, \boldsymbol{x})$.

This can also be easily extended to include a discrete variable, namely the unordered variable $Country$. In this case the minimization problem is:

$$\min_{\delta(\boldsymbol{x}^c)} \Big[\log \boldsymbol{C} - \boldsymbol{X}\delta(\boldsymbol{x}^c)\Big]' W(\boldsymbol{x}^c) \Big[\log \boldsymbol{C} - \boldsymbol{X}\delta(\boldsymbol{x}^c)\Big] \tag{5.8}$$

where $\boldsymbol{x}^c = (\boldsymbol{x}, Country)$ and the matrix $\boldsymbol{X}$ is the same as in the case without discrete regressors. $W(\boldsymbol{x}^c)$ is an $nT \times nT$ diagonal matrix containing the product kernels $W(\boldsymbol{x}_i^c, \boldsymbol{x}^c)$ given by:

$$W(\boldsymbol{x}_i^c, \boldsymbol{x}^c) = K_h(\boldsymbol{x}_i, \boldsymbol{x}) L_\lambda(Country_i, Country) \tag{5.9}$$

This product kernel—suggested by Li and Racine (2003)—admits both the case of the continuous regressors and of the unordered discrete variable $Country$. To smooth the variable $Country$ we use the kernel suggested by Aitchison and Aitken (1976), which is given by:

$$L_\lambda(Country_i, Country) = \begin{cases} 1 - \lambda & \text{if } Country_i = Country \\ \frac{\lambda}{P-1} & \text{if } Country_i \neq Country \end{cases} \tag{5.10}$$

where λ is the bandwidth for the discrete unordered variable and P is the number of different values the discrete unordered variable can take. From this problem we obtain the solution:

$$\hat{\delta}(\boldsymbol{x}^c) = \left[\boldsymbol{X}'W(\boldsymbol{x}^c)\boldsymbol{X}\right]^{-1}\boldsymbol{X}'W(\boldsymbol{x}^c)\log\boldsymbol{C} \tag{5.11}$$

5.3.2 Bandwidth Selection - AIC Cross Validation

We select the bandwidth using the methodology of Hurvich et al. (1998). This method is based on the Akaike Information Criterion (AIC, Akaike, 1998). It is a version of the AIC, modified so as to be more appropriate for model selection in the nonparametric setting. The formula for it is:

$$\begin{aligned} AIC_C(h) &= \ln(\hat{\sigma}^2) + \frac{1+\frac{tr(\boldsymbol{H})}{nT}}{1-\frac{tr(\boldsymbol{H})+2}{nT}} \\ \hat{\sigma}^2 &= \frac{1}{nT}\sum_{i=1}^{nT}\left[\log C_i - \hat{g}(\boldsymbol{x}_i)\right]^2 \end{aligned} \tag{5.12}$$

where the matrix $\boldsymbol{H}$ is given by:

$$\boldsymbol{H} = \begin{bmatrix} \frac{K(\boldsymbol{x}_1,\boldsymbol{x}_1)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_1,\boldsymbol{x}_l)} & \frac{K(\boldsymbol{x}_1,\boldsymbol{x}_2)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_1,\boldsymbol{x}_l)} & \cdots & \frac{K(\boldsymbol{x}_1,\boldsymbol{x}_n)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_1,\boldsymbol{x}_l)} \\ \frac{K(\boldsymbol{x}_2,\boldsymbol{x}_1)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_2,\boldsymbol{x}_l)} & \frac{K(\boldsymbol{x}_2,\boldsymbol{x}_2)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_2,\boldsymbol{x}_l)} & \cdots & \frac{K(\boldsymbol{x}_2,\boldsymbol{x}_n)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_2,\boldsymbol{x}_l)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{K(\boldsymbol{x}_n,\boldsymbol{x}_1)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_n,\boldsymbol{x}_l)} & \frac{K(\boldsymbol{x}_n,\boldsymbol{x}_2)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_n,\boldsymbol{x}_l)} & \cdots & \frac{K(\boldsymbol{x}_n,\boldsymbol{x}_n)}{\sum_{l=1}^{nT}K(\boldsymbol{x}_n,\boldsymbol{x}_l)} \end{bmatrix} \tag{5.13}$$

5.3.3 Model Specification Test - Full Parametric against Full Nonparametric

Naturally, when employing a nonparametric approach, one is interested in knowing whether the additional effort is worth while. In other words, one is interested in testing whether the nonparametric approach represents an improvement over a parametric model. A specification test, of the null hypothesis of a full parametric specification against a full nonparametric specification, is described in Hsiao et al. (2007). This test has the form of a conditional moment test— similar to that in Zheng (1996)—where the null hypothesis is:

$$H_0: \quad \mathrm{P}\left[\mathrm{E}(\log C_i|\boldsymbol{x}_i) = m(\boldsymbol{x}_i,\beta)\right] = 1 \tag{5.14}$$

where $m(\cdot)$ is a known function, β is a vector of unknown parameters and $\boldsymbol{x}_i$ is a vector containing the values of the regressors corresponding to observation i. We want the null of the test to be the full parametric linear specification, so we set $m(\boldsymbol{x}_i,\beta) = \boldsymbol{x}_i'\beta$, i.e., the null we are interested in is:

$$H_0: \quad \mathrm{P}\left[\mathrm{E}(\log C_i|\boldsymbol{x}_i) = \boldsymbol{x}_i'\beta\right] = 1 \tag{5.15}$$

The test statistic is constructed through the sample analogue of:

$$I \stackrel{\text{def}}{=} \mathrm{E}[u_i\, \mathrm{E}(u_i|\boldsymbol{x}_i) f(\boldsymbol{x}_i)] \tag{5.16}$$

where $u_i = \log C_i - \boldsymbol{x}_i'\beta$. The sample analogue of this moment condition is:

$$\hat{I}_n = \frac{1}{nT}\sum_{i=1}^{nT} \hat{u}_i \hat{\mathrm{E}}_{-i}(u_i|\boldsymbol{x}_i)\hat{f}_{-i}(\boldsymbol{x}_i) = \frac{1}{(nT)^2}\sum_{i=1}^{nT}\sum_{\substack{j=1\\ j\neq i}}^{nT} \hat{u}_i\hat{u}_j \boldsymbol{W}(\boldsymbol{x}_i, \boldsymbol{x}_j) \tag{5.17}$$

with the subscript $-i$ indicating that it refers to the leave-one-out estimator obtained when observation i is omitted. Additionally, $\boldsymbol{W}(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is a generalized product kernel which allows for the presence of both continuous and discrete variables. The test statistic can then be normalized as follows:

$$\begin{gathered} \hat{J}_n \stackrel{\text{def}}{=} nT|\boldsymbol{h}|^{1/2}\hat{I}_n/\sqrt{\hat{\Omega}} \\ \hat{\Omega} = \frac{2|\boldsymbol{h}|}{(nT)^2}\sum_{i=1}^{nT}\sum_{\substack{j=1\\ j\neq i}}^{nT} \hat{u}_i^2\hat{u}_j^2 \boldsymbol{W}^2(\boldsymbol{x}_i, \boldsymbol{x}_j) \end{gathered} \tag{5.18}$$

where $|\boldsymbol{h}|$ is the product of the bandwidths obtained via a cross-validation procedure for the nonparametric regression of $\log C$ on $\boldsymbol{x}$. The distribution for the test statistic can be obtained via two-point wild bootstrap.

5.3.4 Model Tests - Variable Significance Tests

Often, a paramount issue of interest after estimating a model is whether the explanatory variables are statistically significant. In the case of standard linear parametric models, the usual t-statistics will do the job. In nonparametric models we need to use special procedures to obtain similar tests. We will present the significance tests for nonparametric models in this section. The null hypothesis for the tests in this section is that the variables under test do not affect the dependent variable. We will continue to use the model given by equation 5.2 to illustrate the procedures.

Racine (1997) test for continuous variables

The first test we use is the one proposed by Racine (1997). The starting point for this test is the idea that if a variable is not relevant in explaining the dependent variable, then its marginal effect should be zero over its domain. Letting $\boldsymbol{X}$ be the vector of regressors and $\boldsymbol{X}_{(j)}$ the set of j regressors whose significance we are testing, the null hypothesis of this test can be expressed as:

$$H_0: \quad \mathbf{d} = \frac{\partial\, \mathrm{E}(\log C|\boldsymbol{X})}{\partial \boldsymbol{X}_{(j)}} = \mathbf{0}_j \quad \text{for all } \boldsymbol{x} \tag{5.19}$$

Using an aggregate L_2 norm measure, the null hypothesis can be expressed as:

$$H_0: \quad \lambda = \mathrm{E}\left(\boldsymbol{\iota}'\boldsymbol{\Delta}\right) = 0 \tag{5.20}$$

where $\boldsymbol{\iota}$ is a vector of ones of length j and $\boldsymbol{\Delta}$ is a vector whose elements are the squares of the corresponding elements of **d** (the vector of derivatives with respect to the variables under test). The test statistic is constructed using a sample analogue of λ:

$$\hat{\lambda} = (nT)^{-1} \sum_{i=1}^{nT} \sum_{j} \left[\hat{\beta}_h(\boldsymbol{x}_i)\right]^2 \tag{5.21}$$

where $\hat{\boldsymbol{\beta}}(\boldsymbol{x}_i)$ is the estimated gradient vector at point $\boldsymbol{x}_i$, and the second summation sums the gradients corresponding to the j variables which significance we are testing. This test statistic is then pivotized in two ways. The first is by dividing the pointwise gradient estimates by the asymptotic approximations to their standard errors (SE), thus obtaining:

$$\hat{\lambda} = (nT)^{-1} \sum_{i=1}^{nT} \sum_{j} \left[\frac{\hat{\beta}_h(\boldsymbol{x}_i)}{SE(\hat{\beta}_h(\boldsymbol{x}_i))}\right]^2 \tag{5.22}$$

The second way in which the test is pivotized is by taking the $\hat{\lambda}$ from equation 5.22 and dividing this test statistic by an estimate of its standard error obtained via nested resampling. The pivotal test statistic is then:

$$\hat{t} = \frac{\hat{\lambda}}{SE(\hat{\lambda})} \tag{5.23}$$

The distribution of the test statistic is then obtained via bootstrap.

Racine et al. (2006) test for Discrete Variables

Now we describe the testing procedure proposed by Racine et al. (2006). Now the starting point is that if a discrete variable has no influence on the dependent variable, then the value it takes makes no difference to the value of the dependent variable. In describing this test we will be using the model given by equation 5.3 instead of of equation 5.2 as the former includes a discrete variable, $Country$. The null for this test can be stated as:

$$H_0: \quad \mathrm{E}(\log C|\boldsymbol{x}, Country) = \mathrm{E}(\log C|\boldsymbol{x}) \text{ almost everywhere} \tag{5.24}$$

where $\boldsymbol{x}$ is the vector of continuous regressors. Considering the way equation 5.3 is written, the null for this test can also be written as:

$$H_0: \quad g(\boldsymbol{x}_i, Country_i = l) = g(\boldsymbol{x}_i, Country_i = 1) \text{ almost everywhere} \quad \text{for } l = 2, \ldots, n \tag{5.25}$$

This suggests that the test be based on:

$$I = \sum_{l=2}^{n} \mathrm{E}\left([g(\boldsymbol{x}, \boldsymbol{Country} = l) - g(\boldsymbol{x}, \boldsymbol{Country} = 1)]^2 \right) \tag{5.26}$$

In fact, I is always non-negative and $I = 0$ if and only if H_0 is true. One can use the nonparametric estimate of $g(\cdot)$ to compute the test statistic:

$$\hat{I} = (nT)^{-1} \sum_{i=1}^{nT} \sum_{l=2}^{n} [\hat{g}(\boldsymbol{x}_i, Country_i = l) - \hat{g}(\boldsymbol{x}_i, Country_i = 1)]^2 \tag{5.27}$$

The distribution of the test statistic is then obtained using bootstrap.

5.4 Data

Our dataset is a panel of yearly observations for 46 countries from 2000 to 2014. The data is mostly the same as in the previous chapters. However, in this chapter we use per capita values, which may be closer to the corresponding concepts in theoretical models. Tables 5.1 to 5.3 report information about the coverage of the dataset, descriptive statistics and correlations.

Table 5.1: List of countries

Armenia	Australia	Austria
Belgium	Bulgaria	Canada
Chile	Cyprus	Czech Republic
Denmark	Estonia	Finland
France	Germany	Greece
Hungary	Iceland	Ireland
Israel	Italy	Jamaica
Japan	Kuwait	Latvia
Lithuania	Luxembourg	Mexico
Netherlands	New Zealand	Norway
Poland	Portugal	Republic of Korea
Romania	Russian Federation	Slovakia
Slovenia	South Africa	Spain
Sweden	Switzerland	Thailand
Ukraine	United Kingdom	United States
Venezuela		

Table 5.2: Descriptive Statistics

Variables	N	mean	sd	min	max
r	690	0.0404	0.0381	-0.02	0.345
FD	690	0.583	0.23	0.098	1
$\log C$	690	14.01	0.833	11.29	15.22
$\log Yd$	690	14.40	0.893	11.61	15.91
$\log W$	690	10.80	1.345	7.012	13.03

Table 5.3: Cross-correlation table

Variables	$\log C$	$\log Yd$	$\log W$	r	FD
$\log C$	1.000				
$\log Yd$	0.982	1.000			
$\log W$	0.956	0.946	1.000		
r	-0.487	-0.487	-0.430	1.000	
FD	0.820	0.799	0.831	-0.431	1.000

The data for household consumption expenditures in constant 2010 prices in local currency was obtained from the National Accounts Main Aggregates Database (United Nations Statistics Division).

We retrieved the data for net disposable income in current local currency from AMECO for Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden, United Kingdom, Norway, Switzerland, United States, Japan, Canada, Mexico, South Korea, Australia, Bulgaria, Latvia, Lithuania, Poland, Czech Republic, Estonia, Hungary, Romania and Slovakia; from OECD for South Africa, New Zealand, Chile and Russia; and for all the other countries we obtained the data from UNdata (http://data.un.org/).

Data on the interbank interest rates was collected from FRED for South Africa, Russia, New Zealand, Norway, Mexico, Israel and Iceland; from the IMF's International Financial Statistics for Kuwait, South Korea, Thailand, Venezuela, Chile, Jamaica, Armenia, Australia, Canada and Switzerland; and from AMECO for all the other countries.

The data for each country's total wealth in current USD comes from Credit Suisse's Global Wealth Databooks.

Our data on credit concerns total credit to the private sector by banks and other financial institutions. The data comes from FRED for Austria, Belgium, Cyprus, Estonia, Finland, France, Greece, Germany, Ireland, Italy, Latvia, Lithuania, Luxembourg, Portugal, Slovakia, Slovenia, Spain, Sweden and Venezuela; from BIS for Canada and New Zealand; and from the World Bank for all other countries.

To obtain the real interest rate we employ the usual formula:

$$\text{real rate} = \frac{1 + \text{nominal rate}}{1 + \text{inflation rate}} - 1 \tag{5.28}$$

We use data on the consumer price index obtained from the World Bank for all countries except Chile and Venezuela (for which we resorted to FRED), to compute the inflation rate.

To obtain the net disposable income and total wealth in real terms, we calculated a consumption deflator using data on consumption expenditure in current prices and consumption expenditure at constant 2010 prices. To convert in USD we use the exchange rates from the National Accounts Main Aggregates Database.

We then compute per capita variables for consumption, disposable income and total wealth by dividing the real, USD measured, versions of each of these variables by each country's population. The data on population is retrieved from the National Accounts Main Aggregates Database for all countries.

As before, the main measure of financial development that we use is the broad-based index of financial development from Svirydzenka (2016).

5.5 Parametric Model Results

We next present the results obtained from a estimating a fully parametric model. These results will serve as benchmarks to be compared with the results obtained from the nonparametric setting, reported in the next sections. The parametric results are obtained using the resources available from the *plm* package (Croissant and Millo, 2008; Millo, 2017; Croissant and Millo, 2019) for R (R Core Team, 2018).

Table 5.4 shows the results from the parametric estimation, together with robust standard errors computed according to the methodology proposed by Arellano (1987). The results from this estimation can be considered standard. Positively signed and statistically significant coefficients for income and lagged consumption. A negative and non significant coefficient for the interest rate and a positive and non significant coefficient for wealth. Regarding financial development, we observe a positive and statistically significant coefficient, suggesting a positive effect on consumption.

Table 5.4: Parametric Model Estimations - Level

	$\log Y$	r	$\log W$	FD	$\log C_{t-1}$
Coefficients	0.292***	-0.07	0.004	0.18***	0.593***
	(0.065)	(0.086)	(0.013)	(0.052)	(0.045)
R^2	0.95437				

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.6 Nonparametric Regression Results

In this section we report the results from the nonparametric regressions. We used a local linear regression technique, with a second-order Gaussian kernel for the continuous variables and the Aitchison and Aitken (1976) kernel for the unordered discrete variable. The bandwidths are chosen according to the Kullback-Leibler cross-validation criterion proposed by Hurvich et al. (1998). The results in this section were obtained using the resources available from the *np* package for R (Hayfield and Racine, 2008) and from the companion website for Henderson and Parmeter (2015).

5.6.1 Model Specification Tests

We start with the specification tests of the full parametric formulation against the full nonparametric alternative described in section 5.3.3. We performed the test on the following parametric models:

$$\log C_{i,t} = \beta_0 + \boldsymbol{x}'_{i,t}\beta + u_{i,t} \quad (a)$$

$$\log C_{i,t} = \beta_0 + \boldsymbol{x}'_{i,t}\beta + \sum_{i=2}^{n} \gamma_i D_i + u_{i,t} \quad (b)$$

where D_i is a dummy variable for country i, taking the value 1 if the observation belongs to that country and zero otherwise. The vector $\boldsymbol{x}_{i,t}$ includes all the five regressors in equation 5.1. We also performed the specification test on the two models but without including financial development:

$$\log C_{i,t} = \alpha_0 + \alpha_1 \log C_{i,t-1} + \alpha_2 \log Y_{i,t} + \alpha_3 r_{i,t} + \alpha_4 \log W_{i,t} + u_{i,t} \quad (c)$$

$$\log C_{i,t} = \alpha_0 + \alpha_1 \log C_{i,t-1} + \alpha_2 \log Y_{i,t} + \alpha_3 r_{i,t} + \alpha_4 \log W_{i,t} + \sum_{i=2}^{n} \gamma_i D_i + u_{i,t} \quad (d)$$

The results reported below use the kernels and cross-validation procedures that we described previously. The results of the tests presented in table 5.5 show a strong rejection of all these parametric specifications in favor of a nonparametric approach.

Table 5.5: Specification Test: Parametric Vs Nonparametric

	$\hat{J}_n$	p-value $\hat{J}_n$	$\hat{I}_n$	p-value $\hat{I}_n$
(a)	11.00177	<0.01	0.000677596	<0.01
(b)	3.271321	<0.01	3.114639e-25	<0.01
(c)	10.03658	<0.01	0.0002776541	<0.01
(d)	2.944552	<0.01	5.672664e-22	<0.01

5.6.2 Bandwidths

Next we report on the bandwidths we used in estimating our model. Additionally we report a rule-of-thumb upper bound for the bandwidths. For continuous variables, this upper bounds is equal to two times the standard deviation of the variable. This follows the suggestion from Hall et al. (2007). Hall et al. (2007) argue that a cross-validation method will select very large smoothing values (larger than a few standard deviations) for variables for that enter linearly in a model estimated by LLLS. For the discrete variable the upper bound is given by $(P-1)/P$. In this case, if the variable hits the upper bound this means that the variable is irrelevant in the model estimated by LLLS.

The bandwidths we obtained for the models based on equation 5.3, to be estimated, are reported in table 5.6, along with the upper bounds. We see that for income, lagged consumption and financial development, the estimated bandwidths are below the upper bounds, providing evidence in favor of the hypothesis that these variables influence consumption in a nonlinear way. As for the interest rate and wealth, they both have estimated bandwidths above the upper bound in the local linear model. This suggests that they enter the model in a way very close to linear.

Table 5.6: Estimated Bandwidths

	Bandwidth	Upper Bound
$\log Y$	0.4514489	1.785848
r	9961.249	0.07622143
$\log W$	5.174115	2.689071
FD	0.1997039	0.4603637
$\log C^l$	0.4106287	1.665558
$Country$	0.1084264	0.9783

5.6.3 Variable Significance

Next we present the results of the nonparametric variable significance tests. Table 5.7 shows the p-values of these tests for each of the variables.

Table 5.7: Significance Test

	Non-pivotal	Pivotal
$\log Y$	<0.01	<0.01
r	<0.01	<0.01
$\log W$	0.3609	0.087719
FD	0.5213	<0.01
$\log C_{t-1}$	<0.01	<0.01
$Country$	<0.01	<0.01

The null of this test is interpreted in the same way as the null of the traditional parametric significance test, meaning that a rejection of the null indicates that the variable has a statistically significant impact on the dependent variable. The results of the tests indicate that income, lagged consumption and the interest rate are relevant in explaining consumption. On the other hand, at the 5% level we do not reject the null of the significance test for wealth. As for financial development, the evidence is mixed, with the non-pivotal test failing to reject the null, while the pivotal test does reject it.

5.6.4 Model Interpretation

We now take the results from the previous sections together with the plots in appendices D.1 and D.2 and attempt to interpret the overall results provided by our nonparametric model of consumption. We added to the plots vertical dotted lines that indicate the quartiles of the variable in the x-axis. We also added rugs to the plots to indicate the sample distribution of the variable in the axis near which they are represented. Finally, in the case of the partial plots for lagged consumption, we added a 45 degree line.

We produced two kinds of plots from our estimates: partial regression plots and gradient plots. The partial regression plot shows the estimated consumption function for a set of values of a given regressor, keeping all the other regressors at a specific value. This allows us to observe how consumption behaves in response to each of its regressors individually. Gradient plots show how the derivative of the estimated function with respect to a specific variable varies with that variable, while holding the other regressors constant. This means that the gradient plots show how the marginal effects of each regressor on consumption vary with that regressor.

The effect of lagged consumption on consumption is what one would expect: the gradient is positive wherever it is statistically significant. While not linear, the usual interpretation applies, meaning that larger values of consumption in the previous period are associated with higher consumption in the current period.

Income displays a nonlinear effect, with the gradient also having a positive sign in the part of the domain where it is statistically significant. The effect of the interest rate on consumption likewise shows a nonlinear behavior. In this case, the gradient varies with the values of the other regressors, taking a negative sign for low values of the remaining regressors and a positive sign otherwise. As for wealth, once more the effect is nonlinear. Whenever the effect is statistically significant it is also positive, but with very small values for the gradient.

As for financial development, the effect is linear in the value of financial development, but nonlinear in the value of the other regressors. This means that countries with different levels of economic development experience different effects from financial development. In countries with higher levels of economic development financial development exerts a positive and significant effect on consumption. In countries with low levels of economic development it exerts a negative and significant effect.

We did an additional exercise with a view to studying how the partial plots of the consumption function change as the value of the financial development index varies. This exercise was carried out by plotting the consumption function as a function of each variable, with the other regressors set at their means, with the exception of financial development. We set financial development at its first (Q1), second (Q2), third (Q3) and fourth (Q4) quartiles, corresponding to each of the four panels in figs. D.11 to D.14. (Q4 is the maximum of the index of financial development.) When we do this we observe that there are only very mild differences in the plots as financial development grows. This indicates that most of the effect of financial development on consumption effect is contained in its own gradient. Changes in financial development do not seem to influence consumption through the gradients of the other variables in the model.

In sum, our results from the nonparametric model show a very different picture from the one that is painted by the traditional fully parametric model. In general we find effects that not only are nonlinear in each variable itself, but also that are dependent on the values taken by other variables. For most variables we also see that not only the significance of the effect, but also the sign of this effect is heavily dependent on where in the consumption function we are observing it. Financial development is no exception to these conclusions. We do observe that it can have a positive effect on consumption, but we also find evidence that this effect may only occur in countries with a relatively high level of development.

5.7 Conclusion

The essential role consumption plays in macroeconomics makes it important that one understands what are the variables at play in the determination of its behavior. More so when economies have been deeply shaken by the last financial crisis. Most of the theories of consumption depend to some degree upon the possibility of smoothing consumption expenditures across the consumer's lifetime. This smoothing is mostly done through the financial system. Given the financial system's evolution in the past few decades, and the importance it appears to have gained in the economic structure, it is relevant to ask what impact may these changes have on consumption behavior.

In order to find evidence of links between financial development and consumption we used nonparametric regression techniques on consumption, a set of its typical regressors and a measure of financial development. The nonparametric approach allows us to search for nonobvious and nonlinear links that may exist between financial development and consumption, without having to specify a functional form for that link. Our results point to the existence of a nonlinear effect of financial development on consumption, an effect that varies with the value of the other determinants of consumption. In addition, our results provide evidence that the effects of wealth, income and the interest rate on consumption are also nonlinear.

Chapter 6

Conclusion

In this dissertation we investigated the existence, in the data, of a link between financial development and aggregate consumption. To this end, we analyzed a collection of empirical modeling frameworks for consumption, where we included a measure of financial development as an explanatory variable. All the models are panel data models where the individual units are countries.

We started by looking at how consumption reacts to financial development in a model—a Panel Vector Autoregression model—where both variables are included as endogenous alongside core macroeconomic variables. This approach provides a description of how financial development fits in within the major macroeconomic relations. In particular, it allows us to assess how much difference it makes to take financial development into account in the context of a general, linear macroeconomic model.

The results presented in the PVAR chapter provide evidence that financial development has some impact on macroeconomic variables, most noticeably investment and GDP. The prima facie case for an effect of financial development on consumption is not as strong. Additional analysis suggests that there may be nonlinear effects of financial development on consumption. This additional evidence is based on a split of the sample according to a threshold value for the index of financial development. The sample split reveals that financial development may actually have an effect on consumption which is noticeable in countries where the level of financial development is higher. Furthermore, the nonlinear effect is also detected when the split of the sample depends on the level of economic development (indicated by GDP per capita) or on an indicator of how easy it is to conduct business activities.

Having found evidence of a nonlinear relation between financial development and consumption, our next step was to modify the model to explicitly account for nonlinearity. The literature has studied many forms of modeling nonlinear relations. In this dissertation we employed three of those nonlinear modeling settings: smooth transition, threshold and nonparametric models. In the chapter dedicated to smooth transition modeling, we took a standard error correction specification for aggregate consumption and introduced a smooth transition mechanism into it. The transition variable was a measure of financial development. The model was then estimated by a Panel Smooth Transition Regression procedure. This methodology allows us to see how the coefficients of the consumption model behave when the level of financial development changes. Being an ECM model, it also allows for a distinction between the impacts on the short-run and on the long-run components of consumption behavior. The results in that chapter suggest that the level of financial development influences the way consumption responds to its determinants. As the level of financial development increases, consumption reacts less to the short-run components, i.e., to changes in individual variables. On the other hand, it reacts more to deviations from the long-run equilibrium. This is consistent with the premise that the financial system is important for facilitating consumption smoothing, as described in standard theoretical models.

After analyzing the smooth transition panel ECM model, we moved to a Panel Threshold Regression. This model may be viewed as a limiting case of a smooth transition model, the case when the transition between the regimes at the opposing ends of the transition function occurs very quickly. In fact, the results concerning the smooth transition panel ECM model suggested that. In the Panel Threshold Regression chapter we used a standard specification for consumption growth, allowing it to depend on income, wealth and the interest rate. The basic model was augmented with a threshold mechanism, with the transition variable being the level of financial development. This accounts for the possibility of an indirect effect of financial development on consumption: changes in the level of financial development change the way consumption responds to the other variables. In addition, we also explored the possibility of a direct effect of financial development on consumption by including a measure of financial development in the equation for consumption. The estimates reported in that chapter support the existence of a threshold effect of financial development on consumption. We also find evidence of a direct effect of financial development on aggregate consumption in the regime with higher values of financial development. This echoes one of the conclusions we reached in the PVAR chapter. Moreover, the results indicate that the effect on consumption that we found for financial development may be rooted in financial institution development—as opposed to financial market development—or in the availability of credit—likewise an alternative, narrower measure of financial development. We did not pursue these possibilities here, but they appear to be worthy of future research.

The last nonlinear approach that we employ to study the relation between financial development and consumption makes use of a nonparametric model. The main advantage of the nonparametric regression techniques is that they do not impose any specific functional form on the way the variables relate to each other. Therefore, the use of this methodology can be viewed as a way of broadening the scope of the nonlinear models that we employed in this dissertation. We estimate a nonparametric model for consumption with income, the interest rate, wealth, lagged consumption and financial development as regressors. The nonparametric model is estimated with the local linear least squares estimator. The results favor the hypothesis that financial development exerts an effect on consumption. We find this effect to be nonlinear in the values of the other regressors. More specifically, in countries with lower levels of income and wealth, the effect from increases in financial development on consumption is negative. The opposite is true in countries with higher levels of income and wealth. This suggests that countries with higher development levels tend to get greater benefits from financial development.

Overall, the results presented in this dissertation indicate that financial development matters for economic activity, namely through consumption. Nevertheless, the link between financial development and consumption appears to be nonlinear. The nonlinearity of that effect is related to the level of financial development itself and to the values of the other variables that help explain consumption behavior. In addition, the effect of financial development on consumption may be both direct and indirect. By indirect we mean that financial development affects the response of consumption to the other variables. Analyses of consumption behavior should therefore take the level of financial development into consideration. Future research may focus on the gains from using a broad measure of financial development over narrower ones, particularly credit. This may be useful for gaining further understanding of the role played by the financial system in contemporary economies.

In fact, we believe that this dissertation can be used as a stepping stone for future research. There is still some degree of uncertainty as to the impact of financial development on consumption. There are also alternative models and methodologies that may be useful for studying financial development and consumption. In a globalized world, financial integration among countries is a crucial feature and it might be interesting to integrate this into the framework that was applied in this dissertation. A possible way of doing this is to take a step further in the PVAR methodology and allow for interdependence between countries. One problem that may arise along this way is the multiplication of parameters. A Bayesian approach may be helpful for mitigating this problem.

The nonparametric methodology used in the dissertation can also be refined, namely through the use of nonparametric IV techniques. The use of semiparametric methodologies can also provide a valuable complement to the nonparametric estimations by establishing a bridge between these results and the typical parametric specifications. Additionally, the varying coefficient model may also be of interest in view of its closeness to the smooth transition and threshold procedures that were used in this dissertation. A comparison of the results could yield worthwhile conclusions.

The last line of future research which this dissertation suggests to us revolves around consumption modeling itself. The evidence of a link between financial development and consumption raises the issue that most of consumption modeling operates under very strong assumptions regarding the financial system. Further bridging the gap between the theoretical and the empirical models of consumption by making explicit the role of financial development poses a considerable challenge, but would constitute important progress.

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Appendix A

Introduction

A.1 Data Sources for Plots in the Introduction

Table A.1: Data Sources for Introduction Plots

Variable	Series	Source
Consumption	Final consumption expenditure at constant 2010 prices in US Dollars divided by total population	National Accounts Main Aggregates Database
Investment	Gross fixed capital formation (including Acquisitions less disposals of valuables) at constant 2010 prices in US Dollars divided by total population	National Accounts Main Aggregates Database
GDP	Gross Domestic Product at constant 2010 prices in US Dollars divided by total population	National Accounts Main Aggregates Database
Net Interest Margin	Bank net interest margin (%)	World Bank, Global Financial Development Database
Stock Market Capitalization	Stock market capitalization to GDP (%)	World Bank, Global Financial Development Database
Stock Market Total Value Traded	Stock market total value traded to GDP (%)	World Bank, Global Financial Development Database
Stock Market Turnover Ratio	Stock market turnover ratio (%)	World Bank, Global Financial Development Database
Private Credit	Private credit by deposit money banks to GDP (%)	World Bank, Global Financial Development Database
Broad Financial Development	Broad based Financial Development Index	Svirydzenka (2016)
Total Population	Population	National Accounts Main Aggregates Database

Appendix B

Financial Development and Economic Activity: A PVAR model

B.1 Variance Decomposition for the Base Model

The following tables report the forecast error variance decomposition for the base models. Each value represents the share of the variance of the variable indicated on the top-left corner of the table that is explained by the variable in the column at the step indicated in the row.

d_l_fd	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	0.934	0.011	0.000	0.005	0.032	0.0002	0.007	0.011
10	0.928	0.011	0.000	0.005	0.037	0.0002	0.007	0.011

d_l_Y	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.001	0.999	0.000	0.000	0.000	0.000	0.000	0.000
5	0.03	0.953	0.005	0.0001	0.009	0.0002	0.001	0.002
10	0.03	0.95	0.005	0.0002	0.013	0.0002	0.001	0.002

d_l_C	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.005	0.133	0.862	0.000	0.000	0.000	0.000	0.000
5	0.006	0.178	0.813	0.0002	0.001	0.0002	0.0003	0.001
10	0.006	0.178	0.813	0.0002	0.002	0.0002	0.0003	0.001

d_l_I	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.001	0.144	0.034	0.821	0.000	0.000	0.000	0.000
5	0.012	0.189	0.032	0.763	0.001	0.001	0.001	0.001
10	0.012	0.19	0.032	0.763	0.001	0.001	0.001	0.001

d_l_P	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.003	0.005	0.0001	0.0001	0.992	0.000	0.000	0.000
5	0.001	0.005	0.0001	0.0003	0.963	0.001	0.02	0.01
10	0.001	0.004	0.0001	0.0003	0.96	0.001	0.022	0.011

d_l_MR	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.027	0.026	0.000	0.001	0.036	0.91	0.000	0.000
5	0.035	0.071	0.001	0.001	0.079	0.801	0.01	0.001
10	0.035	0.071	0.001	0.001	0.084	0.796	0.01	0.001

d_r	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.008	0.009	0.001	0.213	0.017	0.761	0.000
5	0.002	0.007	0.001	0.003	0.292	0.014	0.657	0.025
10	0.002	0.007	0.001	0.003	0.306	0.014	0.643	0.025

d_l_e	d_l_fd	d_l_Y	d_l_C	d_l_I	d_l_P	d_l_MR	d_r	d_l_e
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.006	0.004	0.002	0.097	0.001	0.043	0.847
5	0.001	0.008	0.004	0.004	0.1	0.002	0.041	0.84
10	0.001	0.008	0.004	0.004	0.102	0.002	0.041	0.838

B.2 Controlling for the crisis

B.2.1 Sample without crisis period

Table B.1: Granger causality tests - Sample without crisis period

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.294	0.546	0.126	0.079	0.002	0.113	0.000
d_r	0.181	NA	0.029	0.005	0.088	0.958	0.043	0.168
d_l_MR	0.896	0.226	NA	0.072	0.937	0.159	0.537	0.271
d_l_P	0.007	0.000	0.000	NA	0.420	0.000	0.000	0.000
d_l_I	0.260	0.096	0.066	0.028	NA	0.168	0.526	0.250
d_l_C	0.134	0.471	0.197	0.880	0.847	NA	0.075	0.149
d_l_Y	0.861	0.015	0.473	0.017	0.001	0.000	NA	0.863
d_l_fd	0.216	0.703	0.790	0.361	0.028	0.817	0.113	NA
ALL	0.025	0.000	0.000	0.002	0.002	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.1: IRF - Impulse on Financial Development, Sample without crisis period

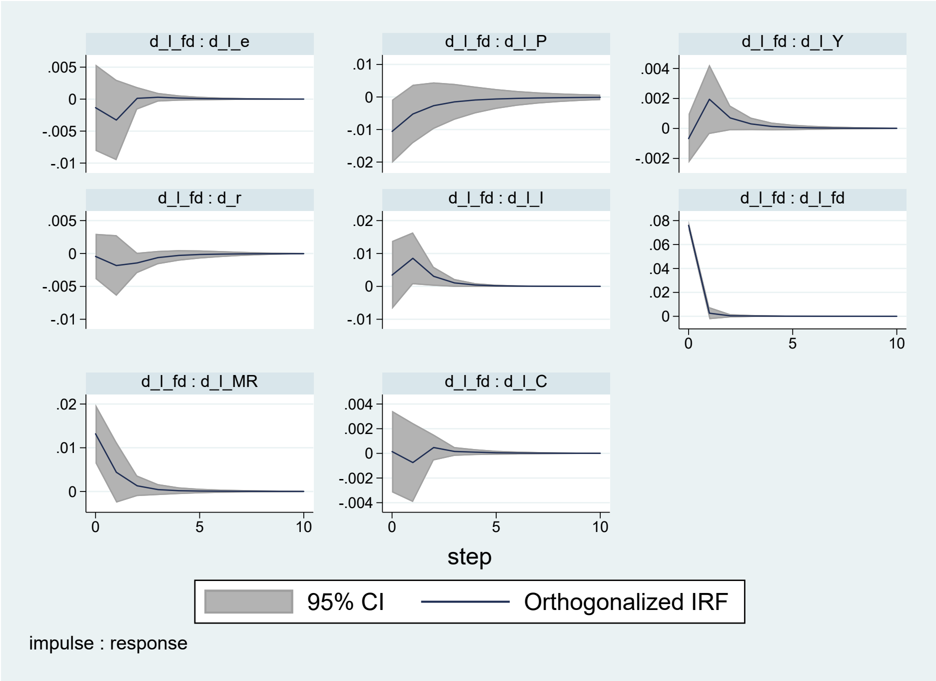


Figure B.2: Cumulative IRF - Impulse on Financial Development, Sample without crisis period

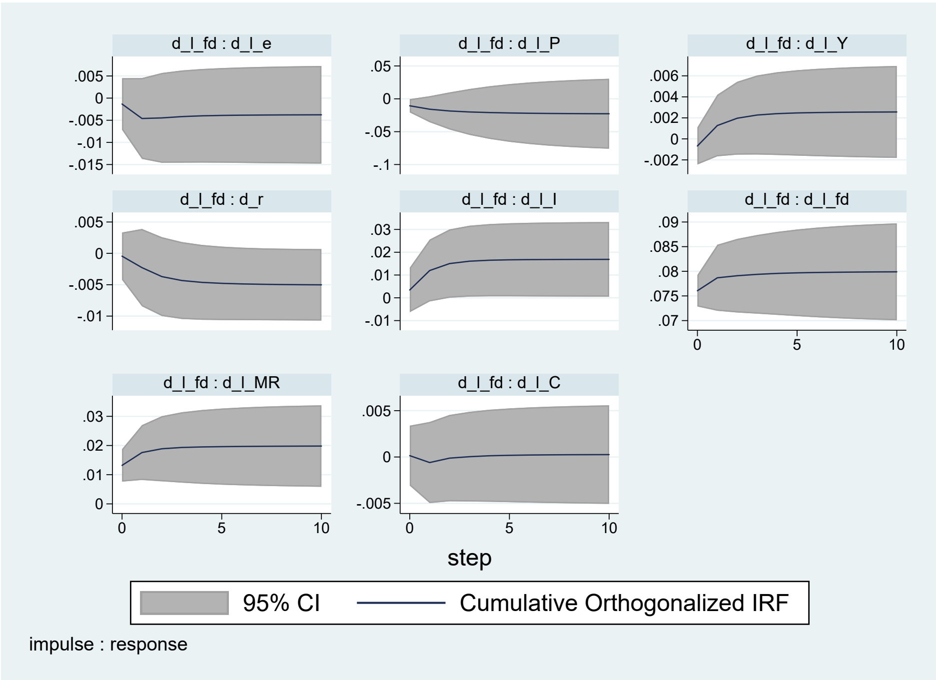


Figure B.3: IRF - Response of Financial Development, Sample without crisis period

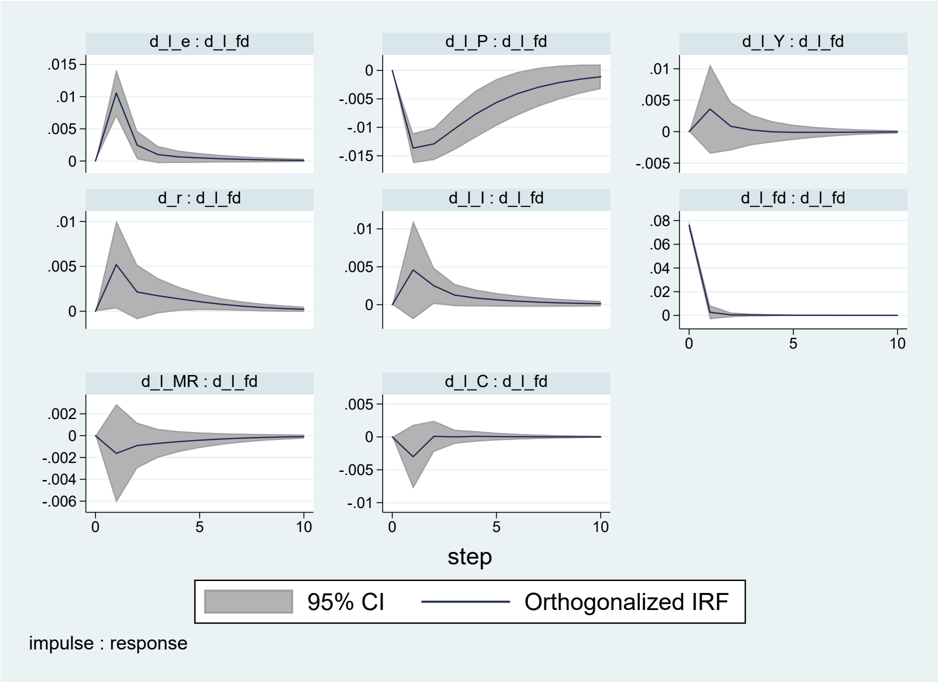
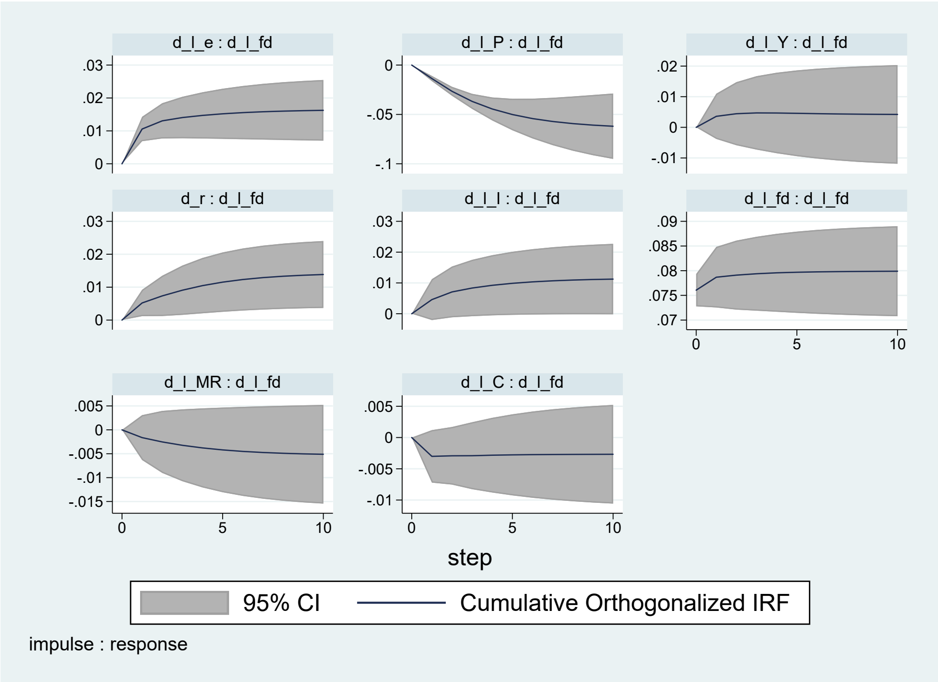


Figure B.4: Cumulative IRF - Response of Financial Development, Sample without crisis period



B.2.2 Controlling for the crisis with a dummy variable

Table B.2: Granger causality tests - Dummy for the crisis periods

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.001	0.689	0.000	0.828	0.205	0.883	0.000
d_r	0.131	NA	0.001	0.001	0.050	0.768	0.075	0.204
d_l_MR	0.506	0.079	NA	0.021	0.194	0.510	0.356	0.067
d_l_P	0.583	0.000	0.005	NA	0.007	0.964	0.000	0.000
d_l_I	0.699	0.144	0.714	0.623	NA	0.474	0.483	0.010
d_l_C	0.605	0.703	0.847	0.281	0.114	NA	0.036	0.842
d_l_Y	0.132	0.305	0.001	0.776	0.841	0.000	NA	0.421
d_l_fd	0.205	0.677	0.093	0.208	0.019	0.792	0.001	NA
ALL	0.103	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.5: IRF - Impulse on Financial Development, Controlling for the crisis with a dummy variable

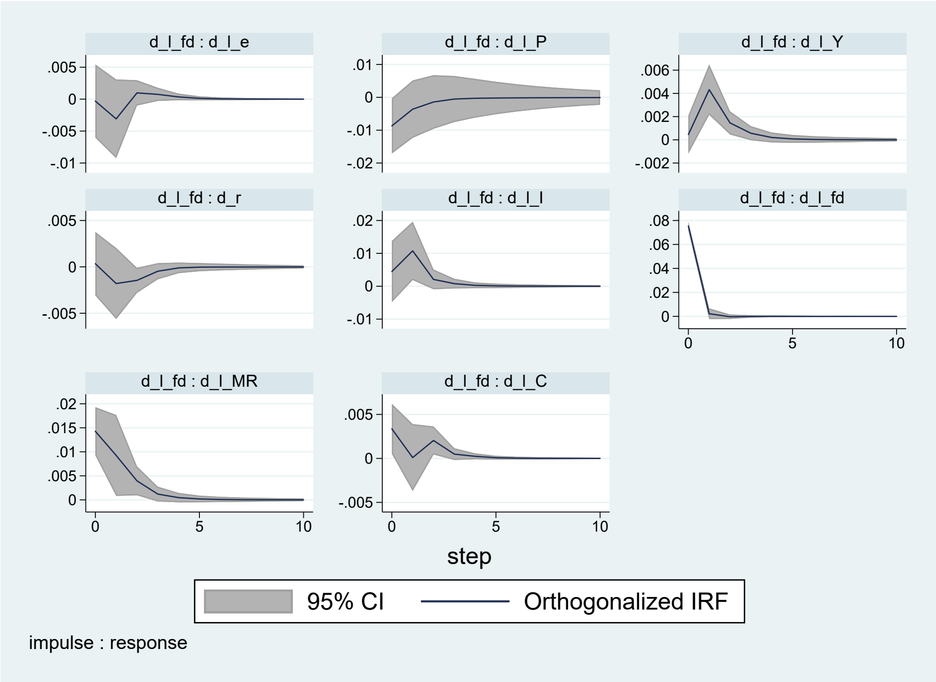


Figure B.6: Cumulative IRF - Impulse on Financial Development, Controlling for the crisis with a dummy variable

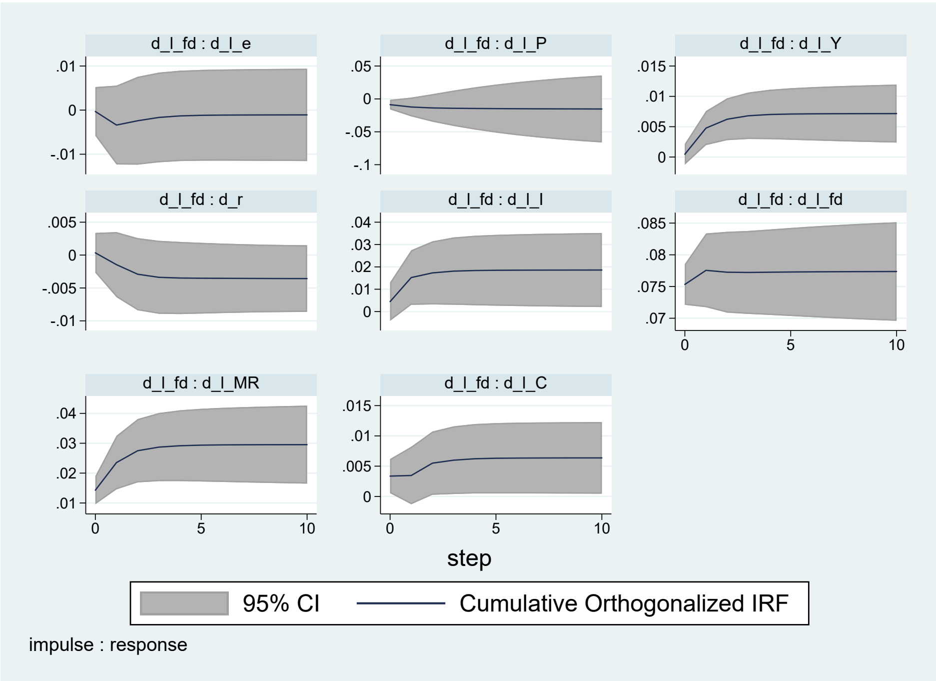


Figure B.7: IRF - Response of Financial Development, Controlling for the crisis with a dummy variable

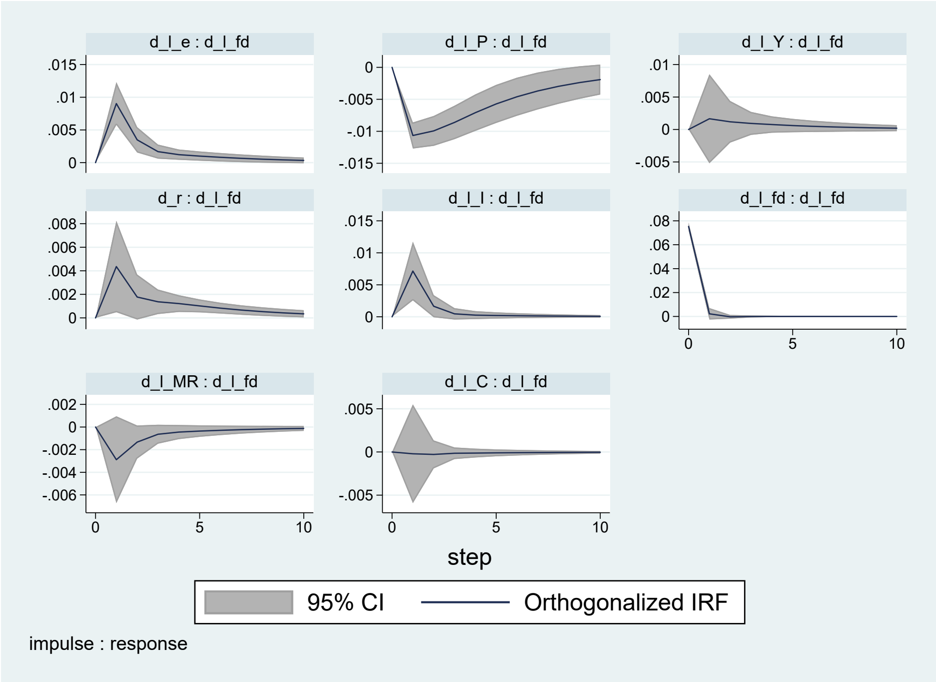
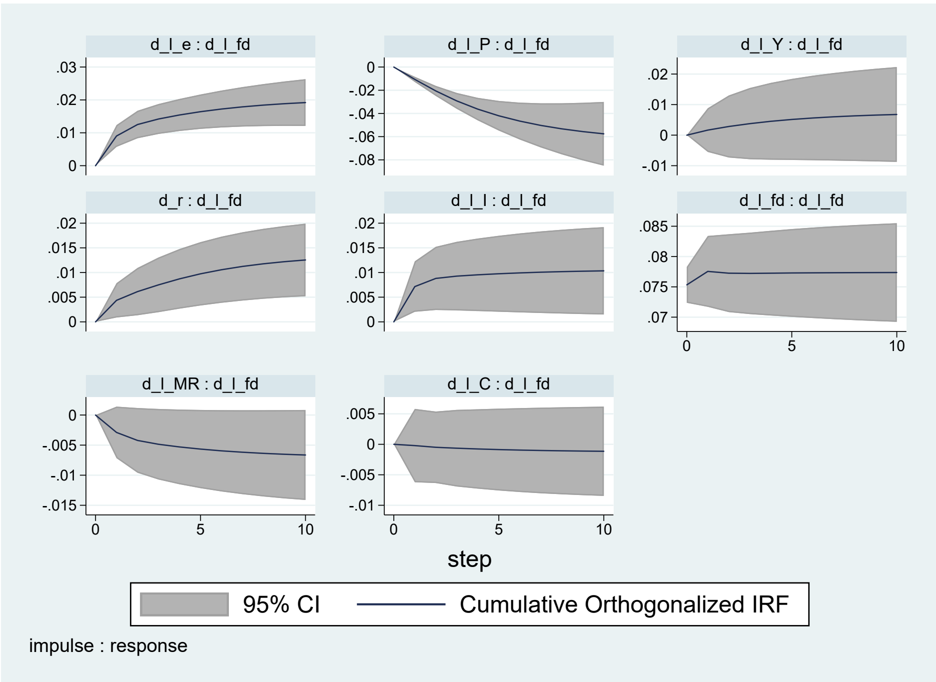


Figure B.8: Cumulative IRF - Response of Financial Development, Controlling for the crisis with a dummy variable



B.3 Level of financial development

B.3.1 Split at 0.52

Table B.3: Granger causality tests - Financial Development above 0.52

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.116	0.195	0.002	0.001	0.000	0.696	0.538
d_r	0.181	NA	0.290	0.000	0.500	0.864	0.885	0.641
d_l_MR	0.975	0.704	NA	0.253	0.336	0.271	0.922	0.647
d_l_P	0.196	0.000	0.012	NA	0.525	0.092	0.596	0.960
d_l_I	0.611	0.000	0.015	0.846	NA	0.642	0.752	0.132
d_l_C	0.209	0.032	0.661	0.048	0.157	NA	0.018	0.001
d_l_Y	0.003	0.954	0.107	0.086	0.000	0.000	NA	0.817
d_l_fd	0.342	0.922	0.931	0.157	0.000	0.000	0.000	NA
ALL	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.9: IRF - Impulse on Financial Development, Financial Development above 0.52

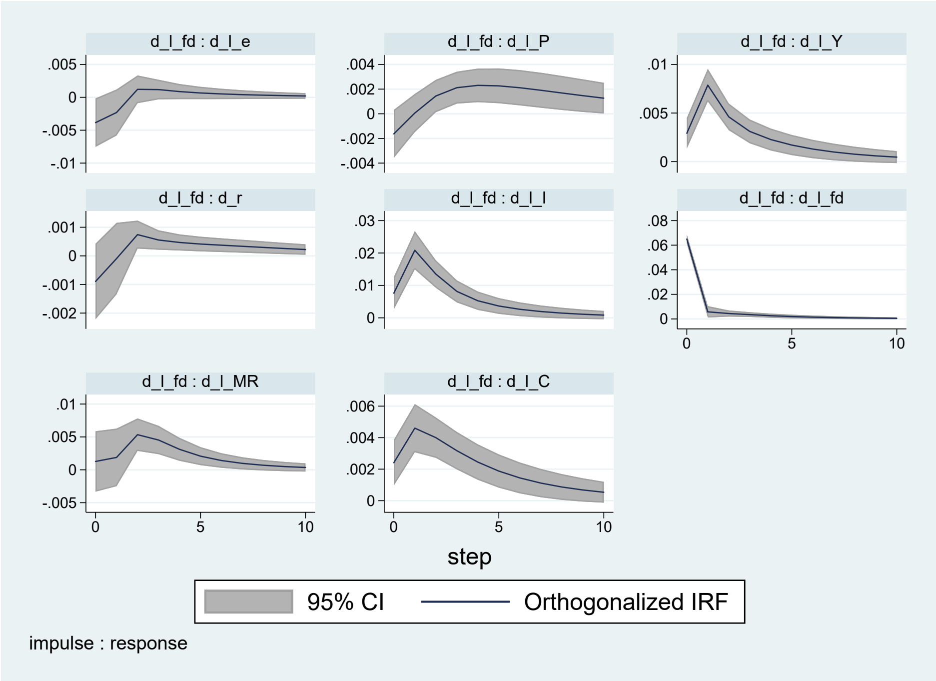


Figure B.10: Cumulative IRF - Impulse on Financial Development, Financial Development above 0.52

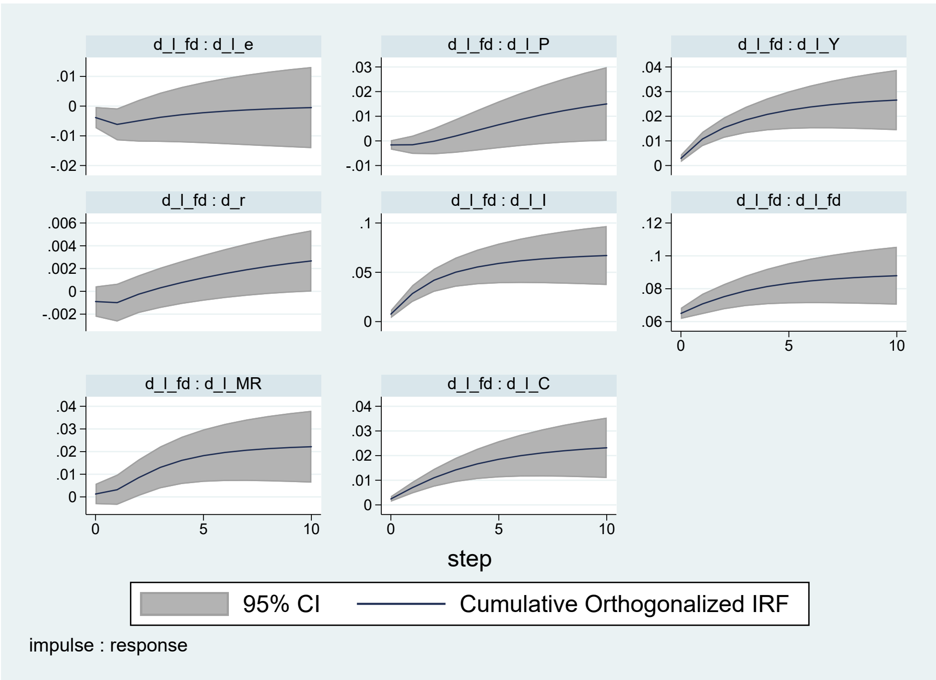


Figure B.11: IRF - Response of Financial Development, Financial Development above 0.52

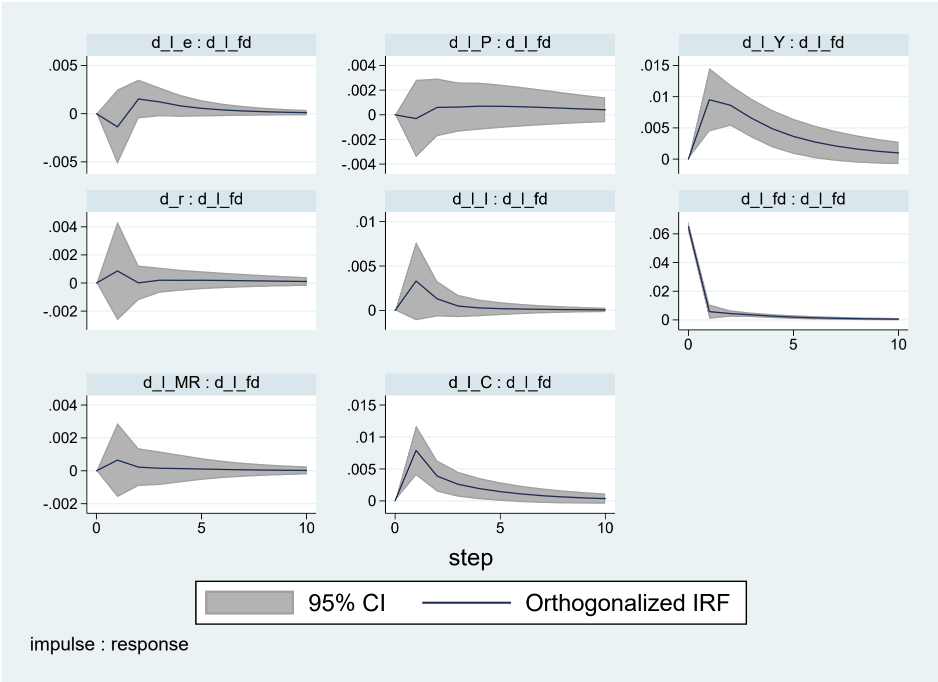


Figure B.12: Cumulative IRF - Response of Financial Development, Financial Development above 0.52

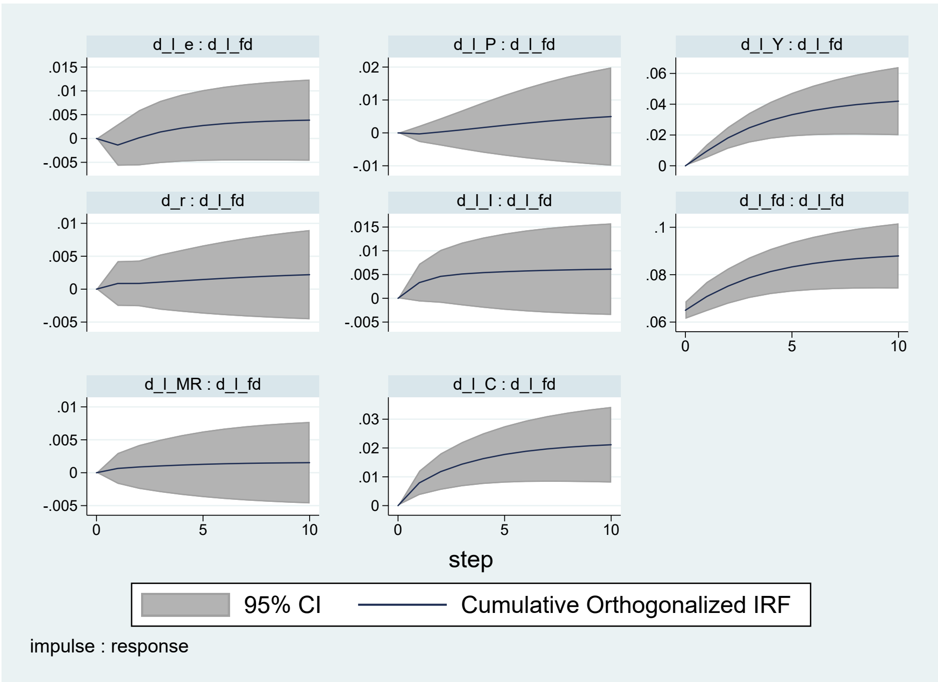


Table B.4: Granger causality tests - Financial Development below 0.52

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.055	0.252	0.033	0.000	0.050	0.248	0.000
d_r	0.091	NA	0.000	0.000	0.779	0.869	0.271	0.002
d_l_MR	0.943	0.003	NA	0.000	0.038	0.533	0.270	0.024
d_l_P	0.001	0.000	0.000	NA	0.252	0.059	0.013	0.000
d_l_I	0.059	0.687	0.700	0.467	NA	0.660	0.892	0.088
d_l_C	0.942	0.992	0.651	0.799	0.357	NA	0.015	0.743
d_l_Y	0.418	0.256	0.101	0.932	0.001	0.024	NA	0.920
d_l_fd	0.038	0.355	0.010	0.222	0.301	0.318	0.296	NA
ALL	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.13: IRF - Impulse on Financial Development, Financial Development below 0.52

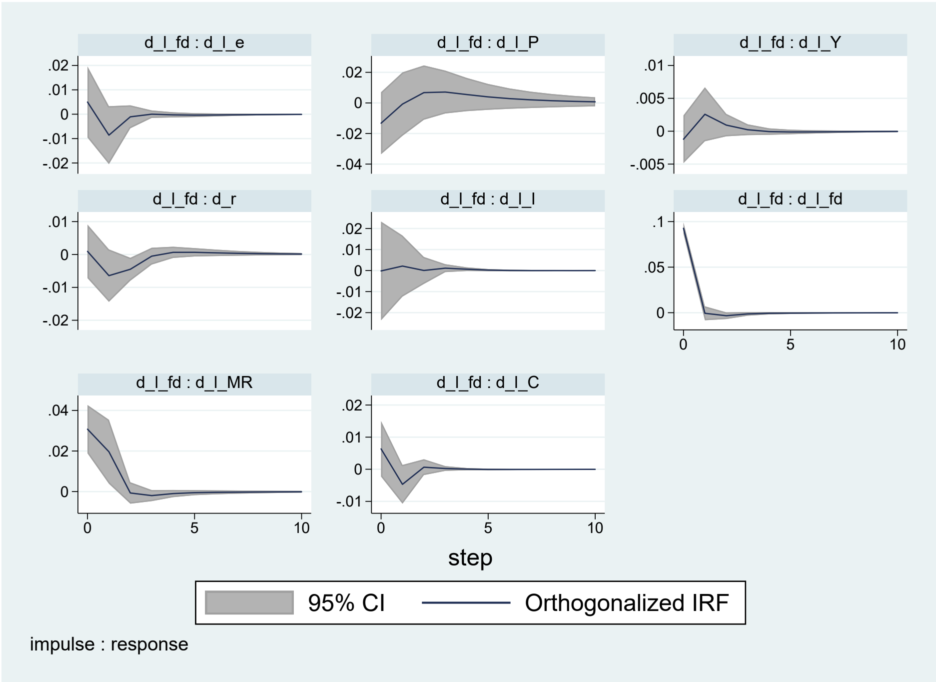


Figure B.14: Cumulative IRF - Impulse on Financial Development, Financial Development below 0.52

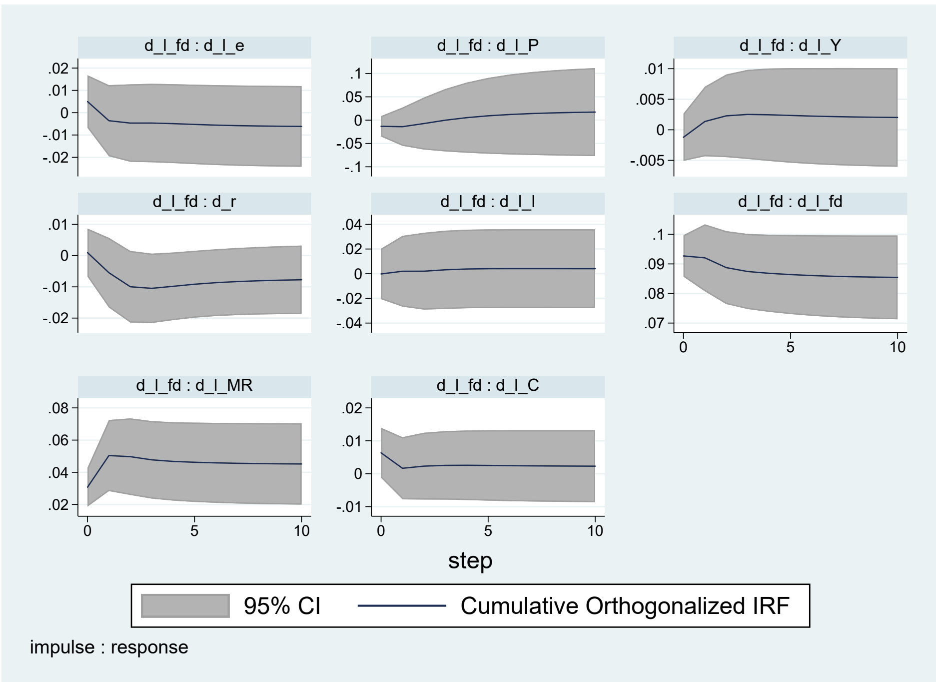


Figure B.15: IRF - Response of Financial Development, Financial Development below 0.52

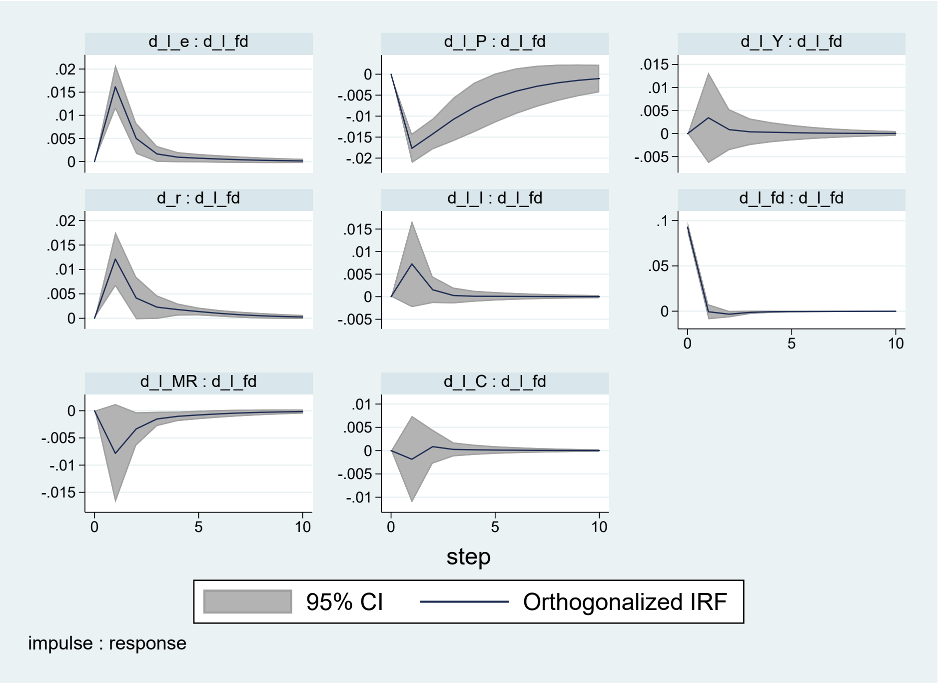
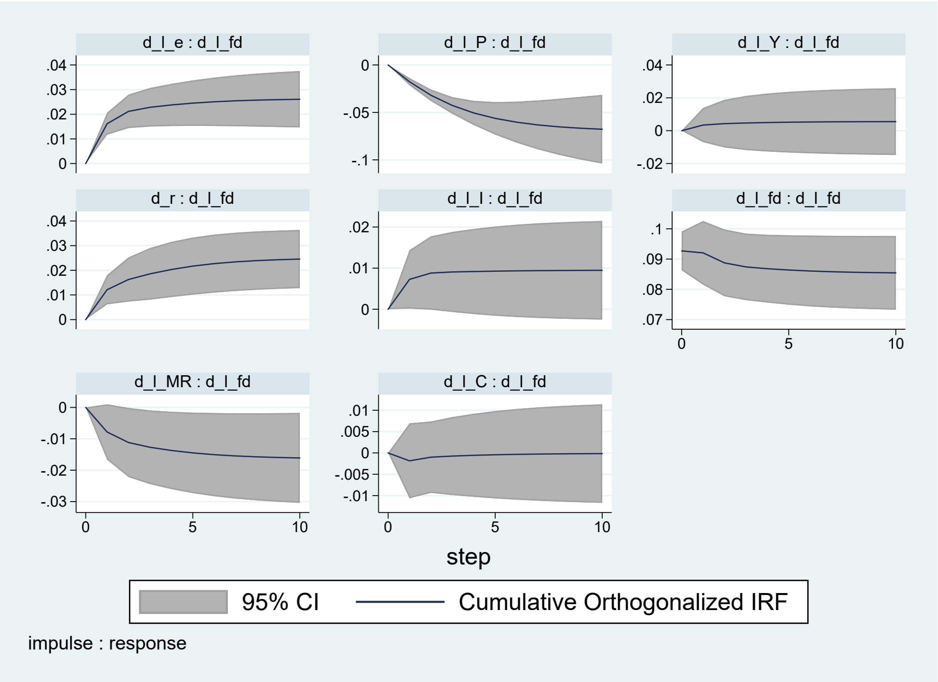


Figure B.16: Cumulative IRF - Response of Financial Development, Financial Development below 0.52



B.3.2 Split at 0.68

Table B.5: Granger causality tests - Financial Development above 0.68

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.025	0.098	0.004	0.000	0.012	0.993	0.667
d_r	0.708	NA	0.326	0.000	0.415	0.770	0.945	0.050
d_l_MR	0.967	0.866	NA	0.485	0.217	0.294	0.959	0.975
d_l_P	0.486	0.000	0.364	NA	0.207	0.494	0.672	0.228
d_l_I	0.780	0.010	0.020	0.889	NA	0.920	0.984	0.001
d_l_C	0.166	0.568	0.518	0.427	0.010	NA	0.103	0.003
d_l_Y	0.015	0.920	0.306	0.108	0.000	0.002	NA	0.078
d_l_fd	0.755	0.923	0.907	0.075	0.000	0.000	0.000	NA
ALL	0.096	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.17: IRF - Impulse on Financial Development, Financial Development above 0.68

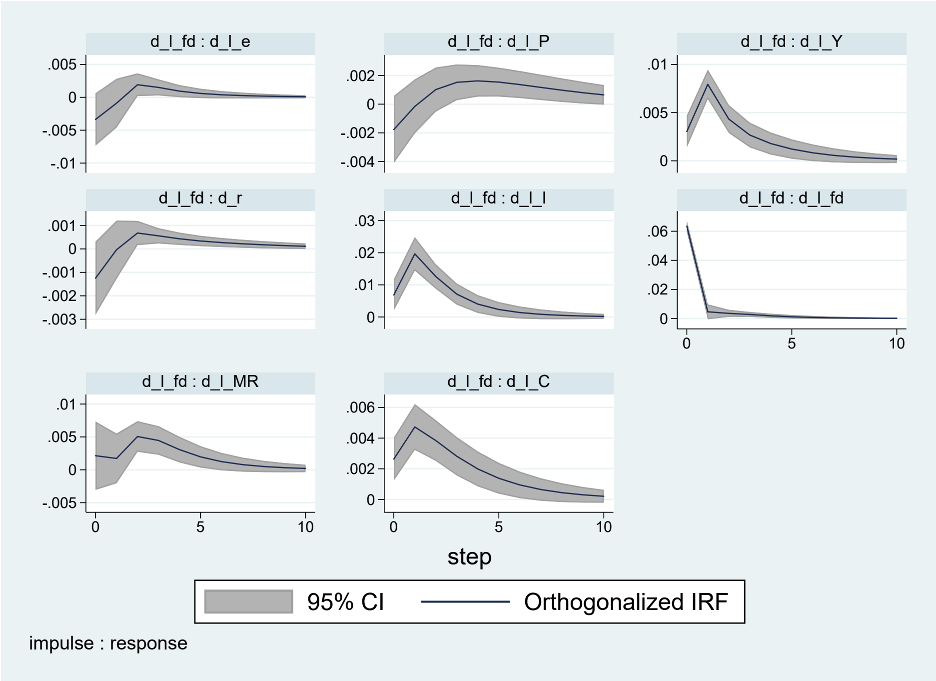


Figure B.18: Cumulative IRF - Impulse on Financial Development, Financial Development above 0.68

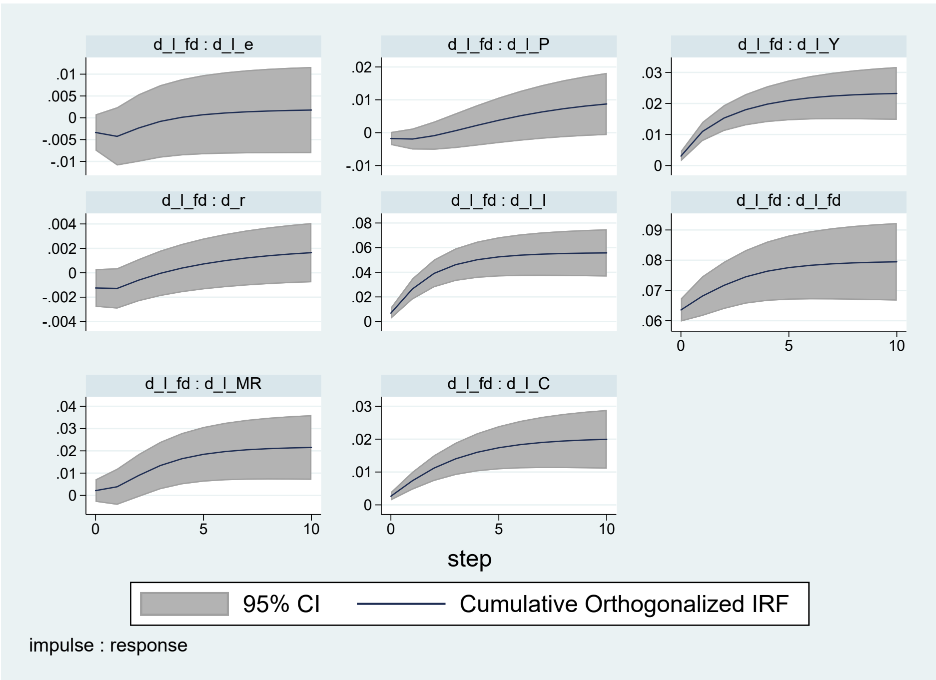


Figure B.19: IRF - Response of Financial Development, Financial Development above 0.68

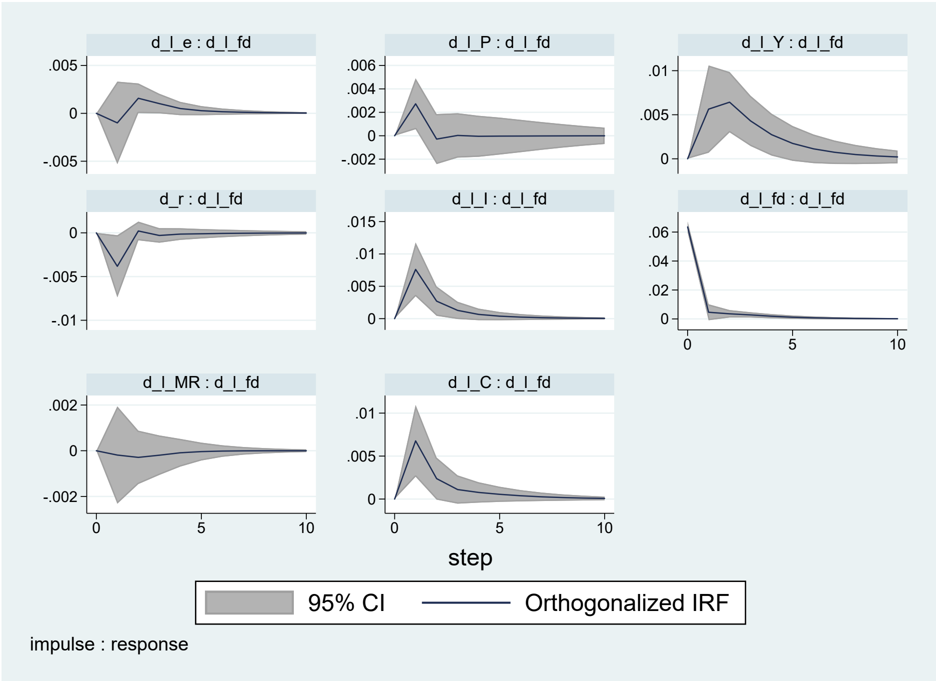


Figure B.20: Cumulative IRF - Response of Financial Development, Financial Development above 0.68

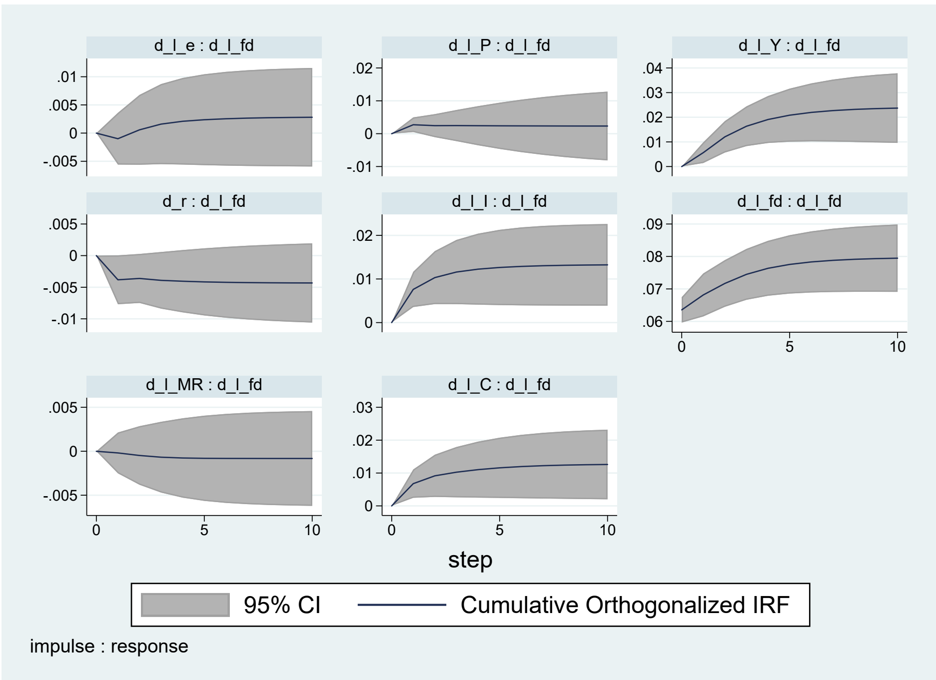


Table B.6: Granger causality tests - Financial Development below 0.68

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.014	0.396	0.011	0.004	0.035	0.378	0.000
d_r	0.062	NA	0.001	0.000	0.818	0.938	0.233	0.001
d_l_MR	0.904	0.004	NA	0.000	0.062	0.472	0.205	0.088
d_l_P	0.003	0.000	0.000	NA	0.162	0.102	0.021	0.000
d_l_I	0.121	0.550	0.733	0.445	NA	0.735	0.941	0.112
d_l_C	0.949	0.923	0.801	0.905	0.315	NA	0.018	0.910
d_l_Y	0.579	0.397	0.014	0.701	0.000	0.005	NA	0.480
d_l_fd	0.037	0.326	0.024	0.117	0.180	0.460	0.169	NA
ALL	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.21: IRF - Impulse on Financial Development, Financial Development below 0.68

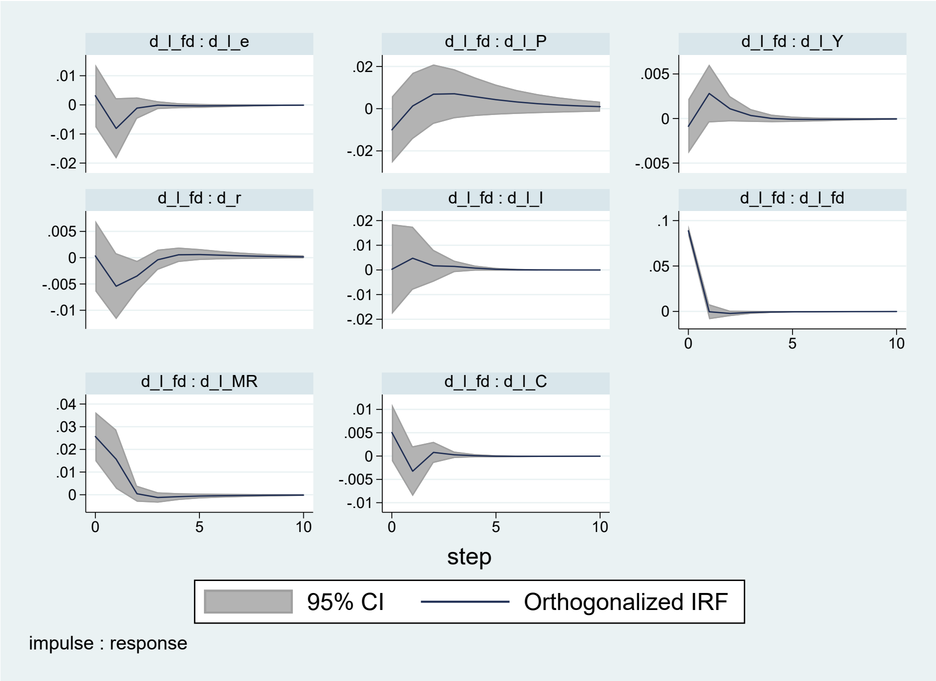


Figure B.22: Cumulative IRF - Impulse on Financial Development, Financial Development below 0.68

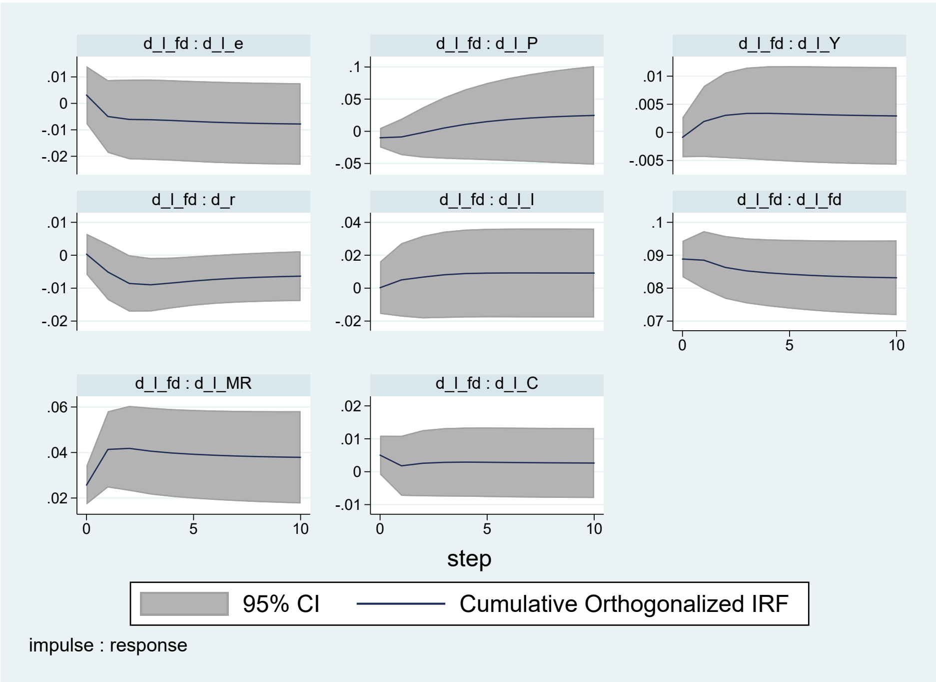


Figure B.23: IRF - Response of Financial Development, Financial Development below 0.68

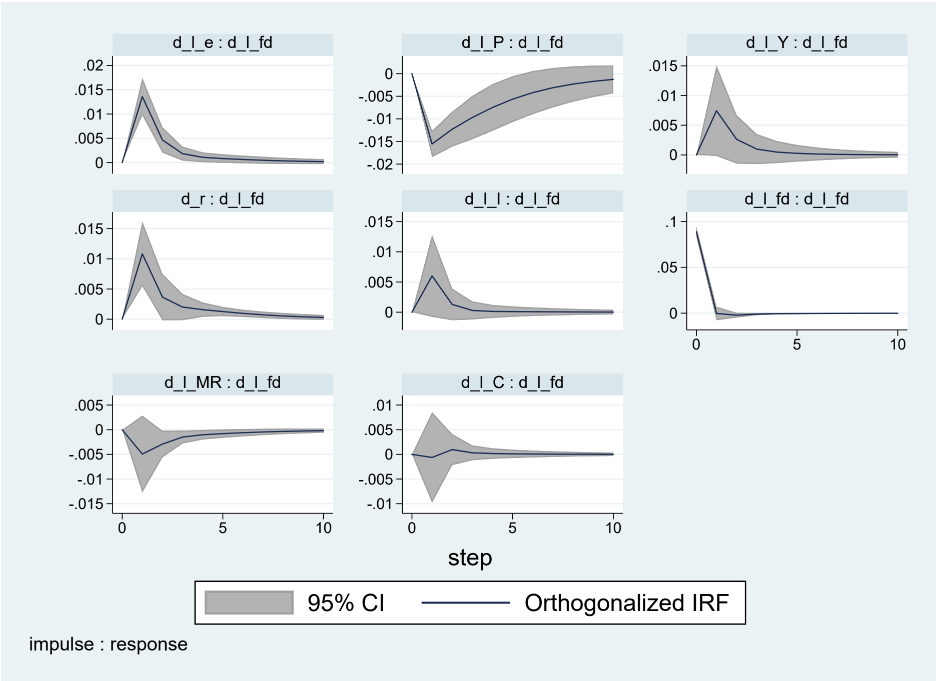
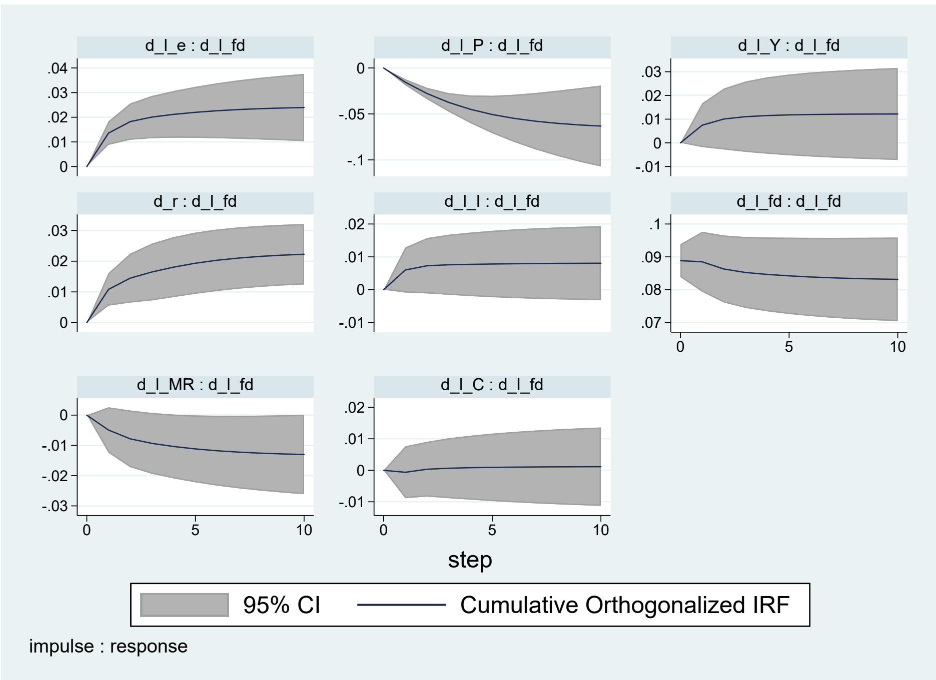


Figure B.24: Cumulative IRF - Response of Financial Development, Financial Development below 0.68



B.3.3 Initial level of financial development

Table B.7: Granger causality tests - Controlling for initial level of financial development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.003	0.774	0.003	0.005	0.448	0.021	0.000
d_r	0.046	NA	0.001	0.000	0.364	0.211	0.136	0.233
d_l_MR	0.434	0.207	NA	0.075	0.243	0.952	0.412	0.380
d_l_P	0.014	0.000	0.000	NA	0.005	0.059	0.000	0.000
d_l_I	0.042	0.255	0.324	0.836	NA	0.877	0.980	0.041
d_l_C	0.558	0.858	0.416	0.812	0.058	NA	0.020	0.920
d_l_Y	0.928	0.903	0.001	0.140	0.000	0.000	NA	0.652
d_l_fd	0.068	0.651	0.171	0.313	0.000	0.591	0.000	NA
ALL	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.25: IRF - Impulse on Financial Development, Controlling for the initial level of financial development

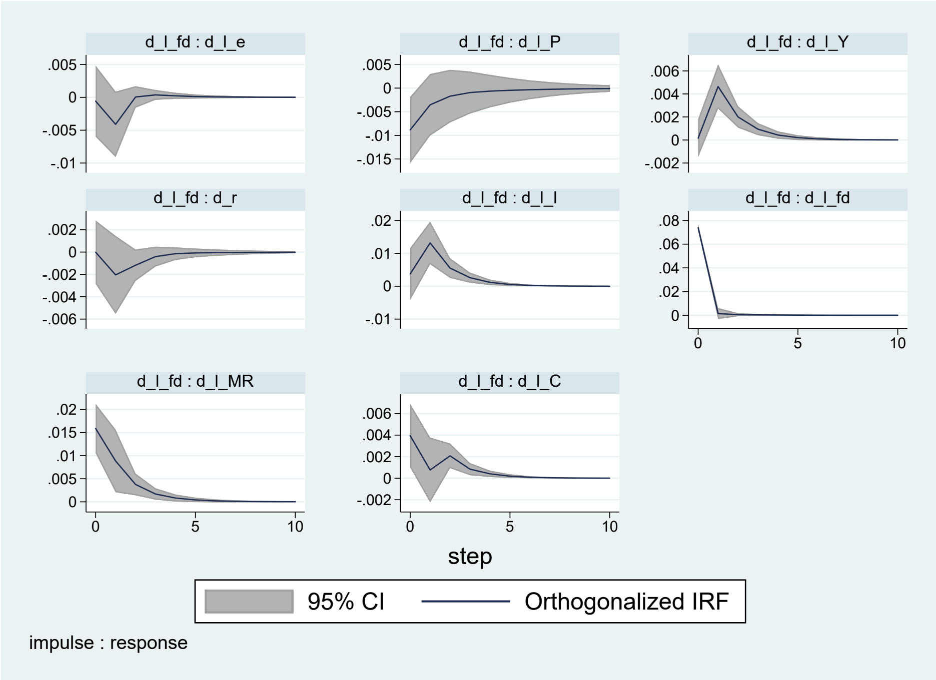


Figure B.26: Cumulative IRF - Impulse on Financial Development, Controlling for the initial level of financial development

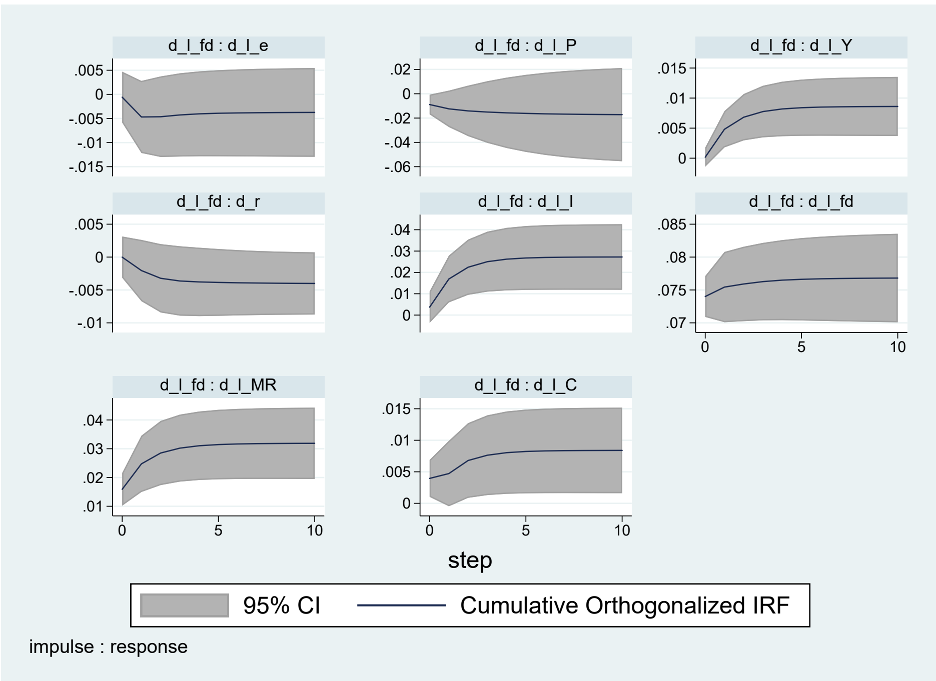


Figure B.27: IRF - Response of Financial Development, Controlling for the initial level of financial development

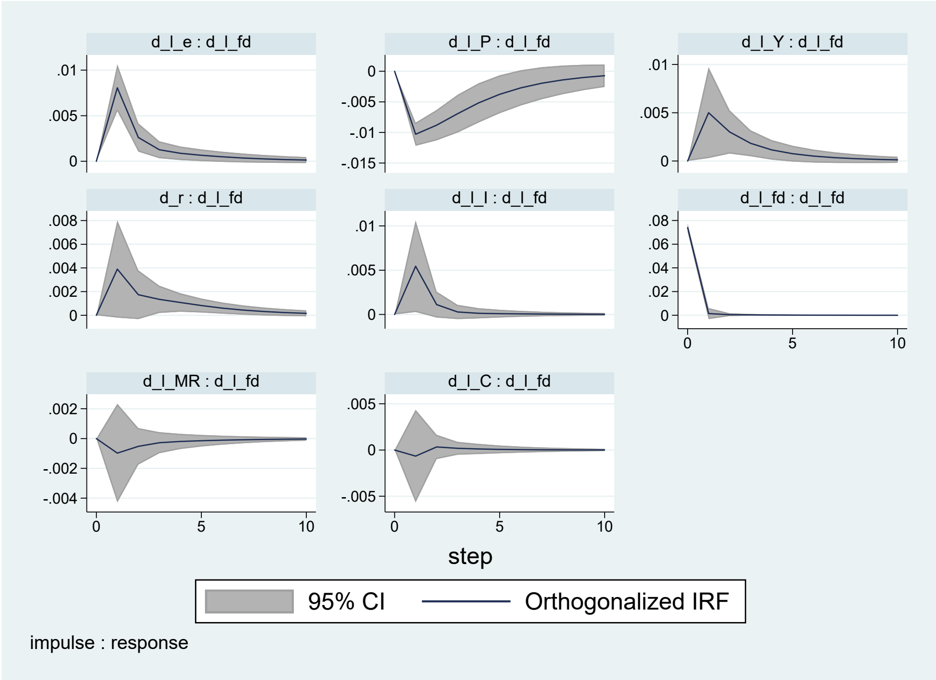
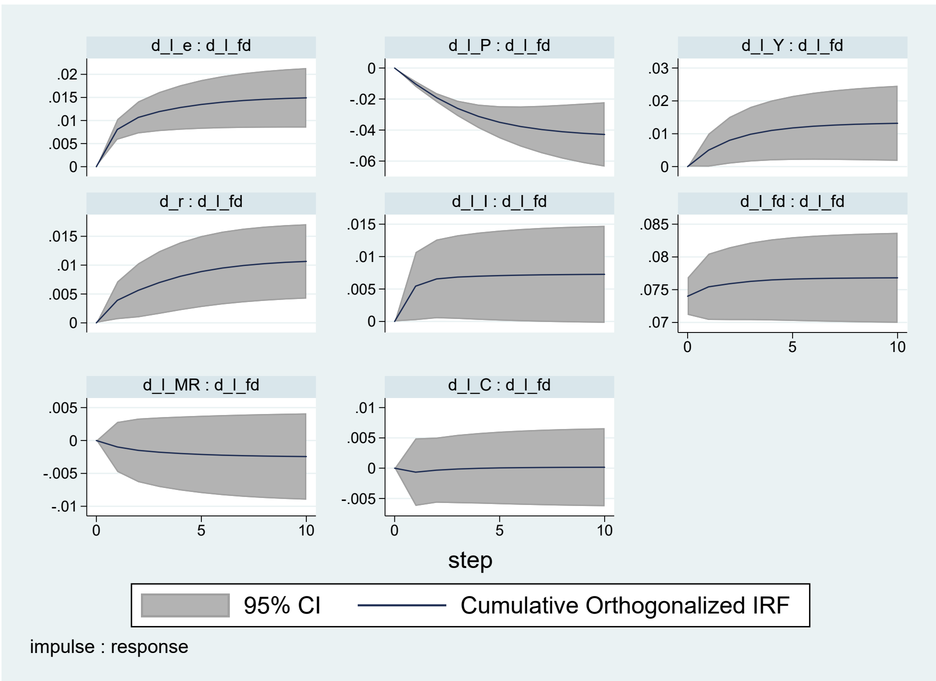


Figure B.28: Cumulative IRF - Response of Financial Development, Controlling for the initial level of financial development



B.4 Alternative Financial Development Measures

B.4.1 Benchmark - reduced sample

Table B.8: Granger causality tests - Benchmark, reduced sample

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.882	0.152	0.522	0.000	0.000	0.730	0.850
d_r	0.915	NA	0.840	0.000	0.000	0.223	0.048	0.304
d_l_MR	0.617	0.001	NA	0.000	0.030	0.785	0.092	0.033
d_l_P	0.000	0.000	0.000	NA	0.000	0.630	0.794	0.000
d_l_I	0.000	0.302	0.193	0.000	NA	0.000	0.158	0.554
d_l_C	0.000	0.770	0.684	0.293	0.056	NA	0.930	0.095
d_l_Y	0.000	0.650	0.577	0.007	0.000	0.000	NA	0.164
d_l_fd	0.823	0.389	0.288	0.083	0.000	0.094	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.29: IRF - Impulse on Financial Development, Benchmark, reduced sample

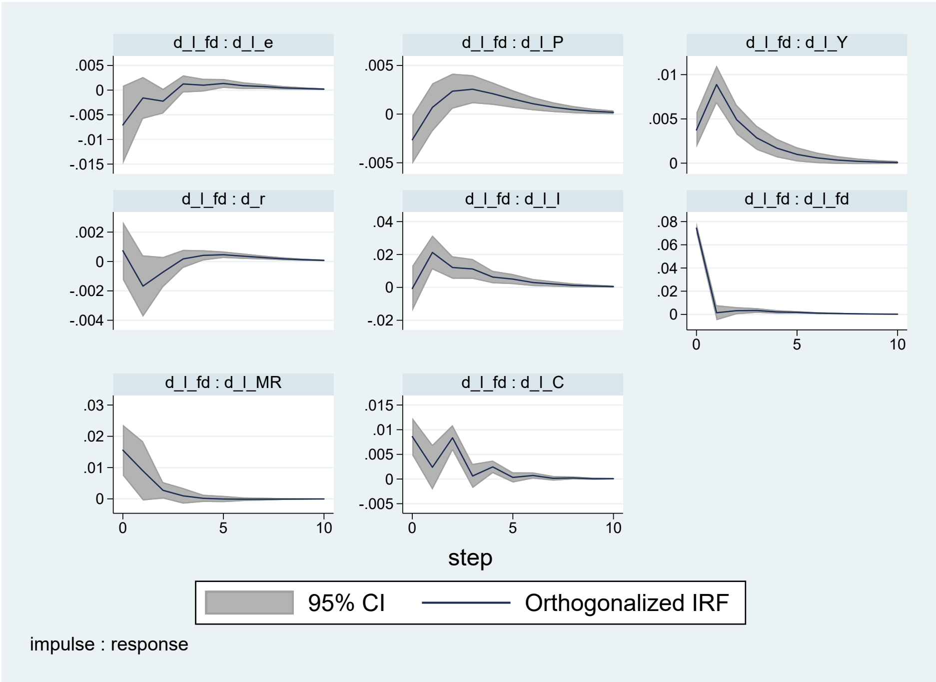


Figure B.30: Cumulative IRF - Impulse on Financial Development, Benchmark, reduced sample

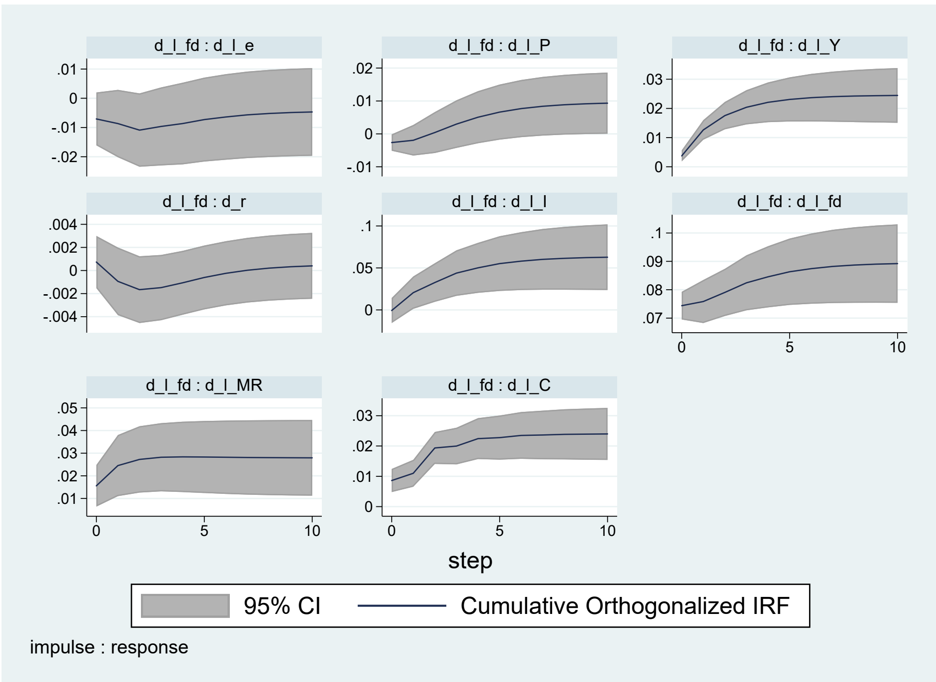


Figure B.31: IRF - Response of Financial Development, Benchmark, reduced sample

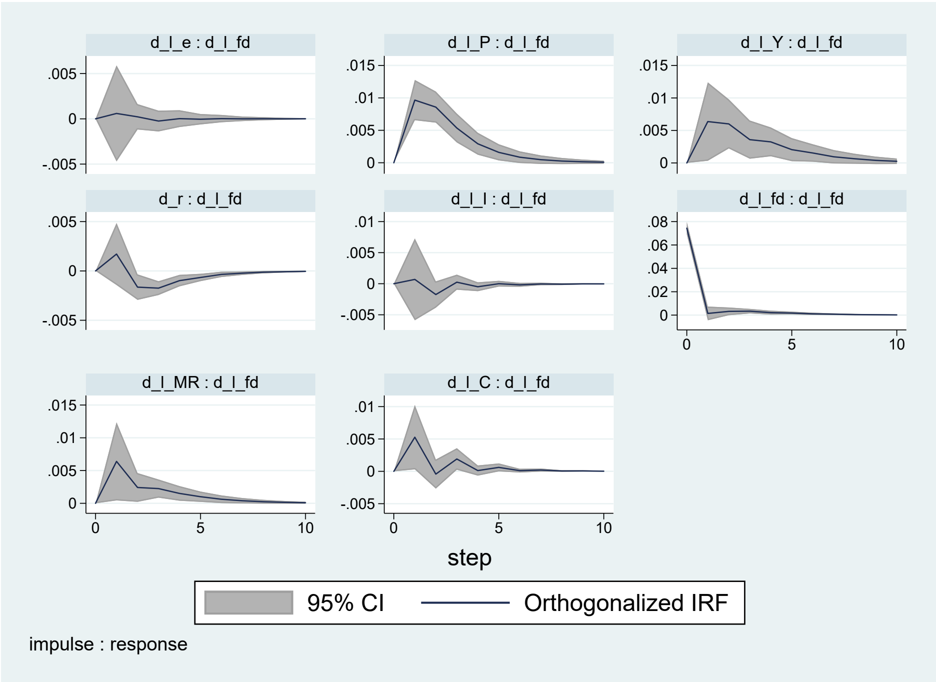


Figure B.32: Cumulative IRF - Response of Financial Development, Benchmark, reduced sample

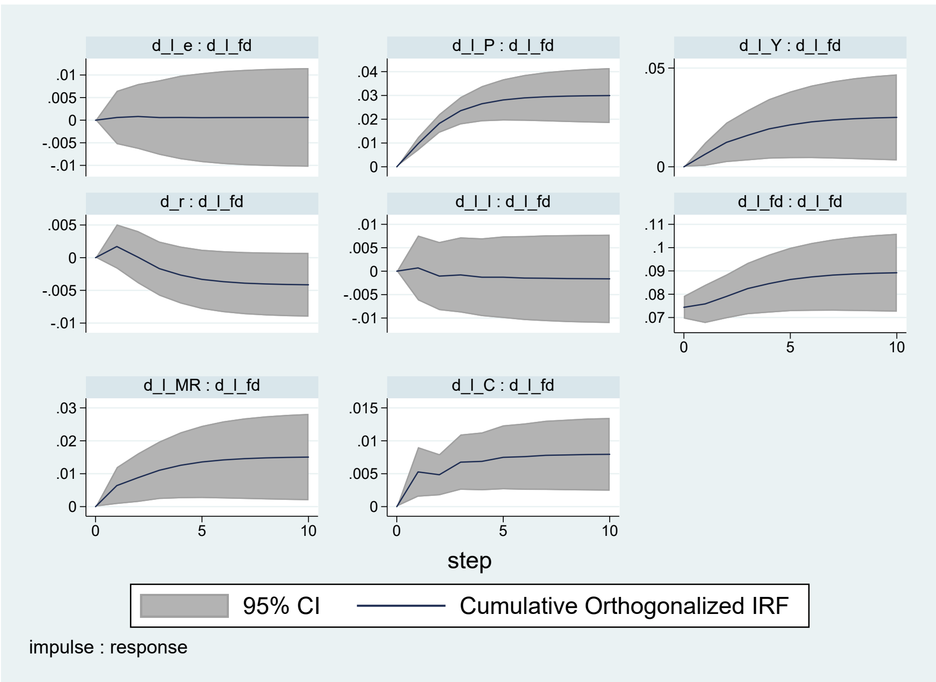


Table B.9: Granger causality tests - Benchmark, reduced sample, “High” Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.265	0.361	0.030	0.102	0.509	0.746	0.207
d_r	0.082	NA	0.647	0.000	0.629	0.735	0.060	0.028
d_l_MR	0.015	0.847	NA	0.752	0.327	0.621	0.402	0.124
d_l_P	0.994	0.000	0.003	NA	0.000	0.889	0.000	0.000
d_l_I	0.166	0.002	0.225	0.335	NA	0.773	0.135	0.608
d_l_C	0.015	0.031	0.991	0.112	0.383	NA	0.076	0.000
d_l_Y	0.000	0.501	0.381	0.004	0.005	0.182	NA	0.222
d_l_fd	0.690	0.082	0.320	0.002	0.000	0.000	0.000	NA
ALL	0.001	0.000	0.001	0.000	0.000	0.001	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.33: IRF - Impulse on Financial Development, Benchmark, reduced sample, "High" Financial Development

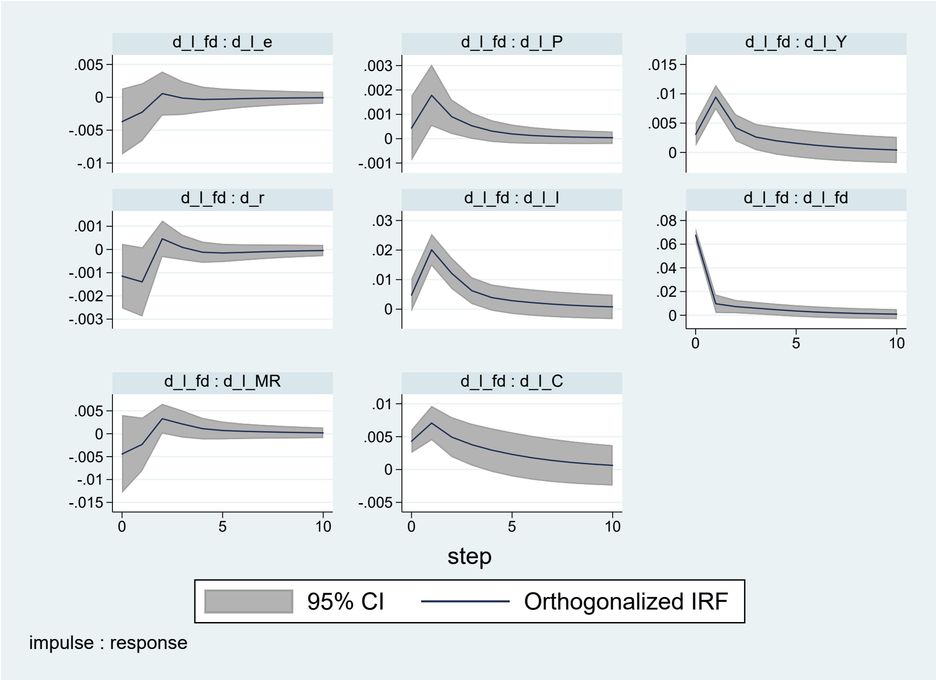


Figure B.34: Cumulative IRF - Impulse on Financial Development, Benchmark, reduced sample, "High" Financial Development

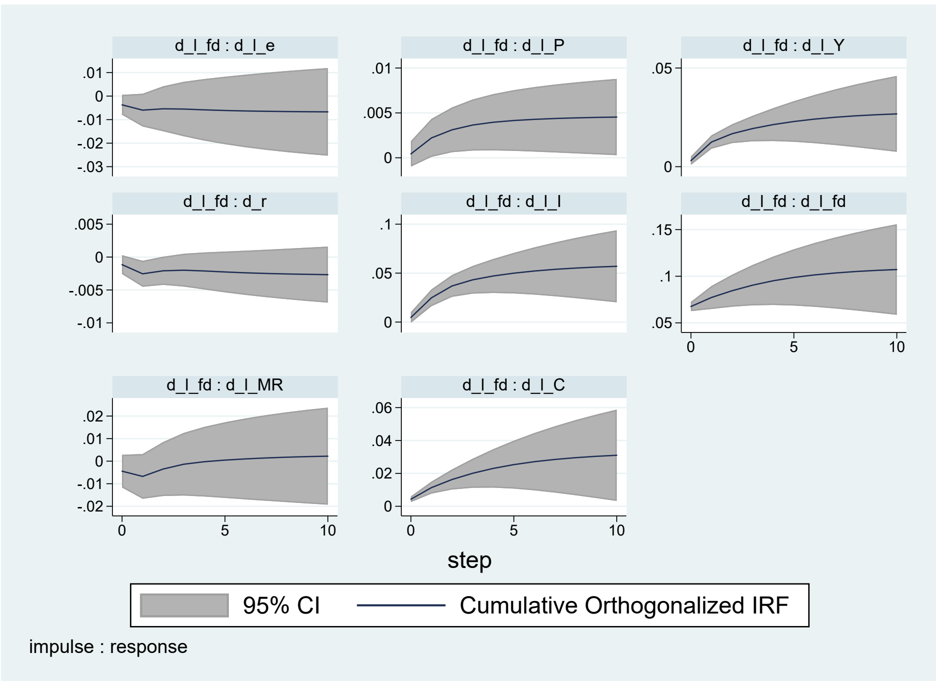


Figure B.35: IRF - Response of Financial Development, Benchmark, reduced sample, “High” Financial Development

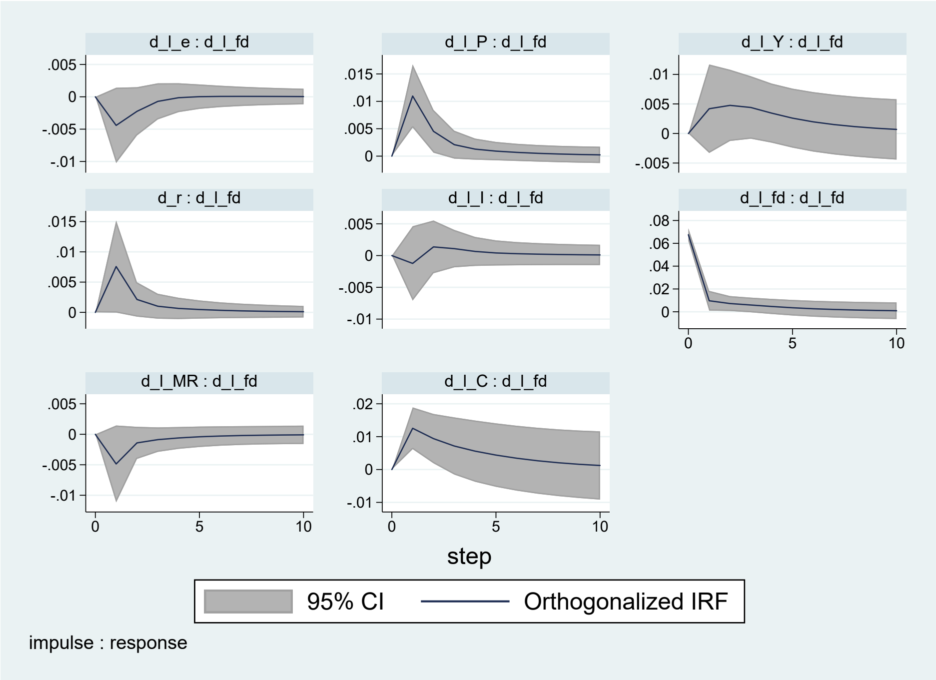


Figure B.36: Cumulative IRF - Response of Financial Development, Benchmark, reduced sample, “High” Financial Development

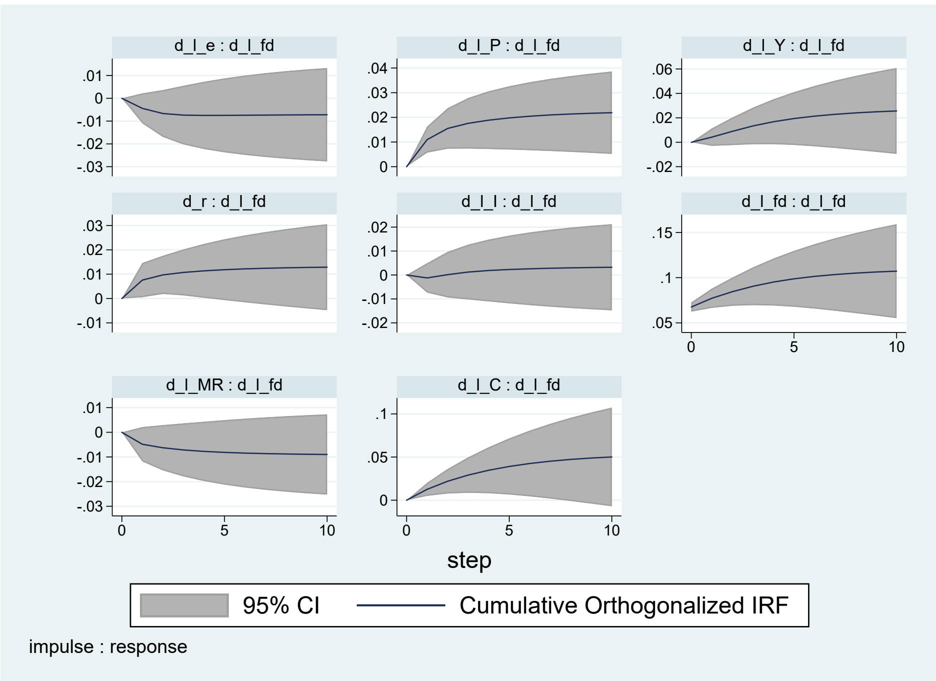


Table B.10: Granger causality tests - Benchmark, reduced sample, "Low" Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.475	0.059	0.890	0.006	0.689	0.021	0.008
d_r	0.363	NA	0.623	0.000	0.000	0.370	0.000	0.140
d_l_MR	0.082	0.000	NA	0.000	0.000	0.670	0.058	0.127
d_l_P	0.000	0.000	0.000	NA	0.000	0.000	0.645	0.214
d_l_I	0.000	0.000	0.099	0.000	NA	0.000	0.078	0.033
d_l_C	0.000	0.564	0.024	0.336	0.001	NA	0.238	0.688
d_l_Y	0.000	0.752	0.061	0.179	0.000	0.000	NA	0.000
d_l_fd	0.270	0.327	0.000	0.423	0.000	0.044	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.37: IRF - Impulse on Financial Development, Benchmark, reduced sample, “Low” Financial Development

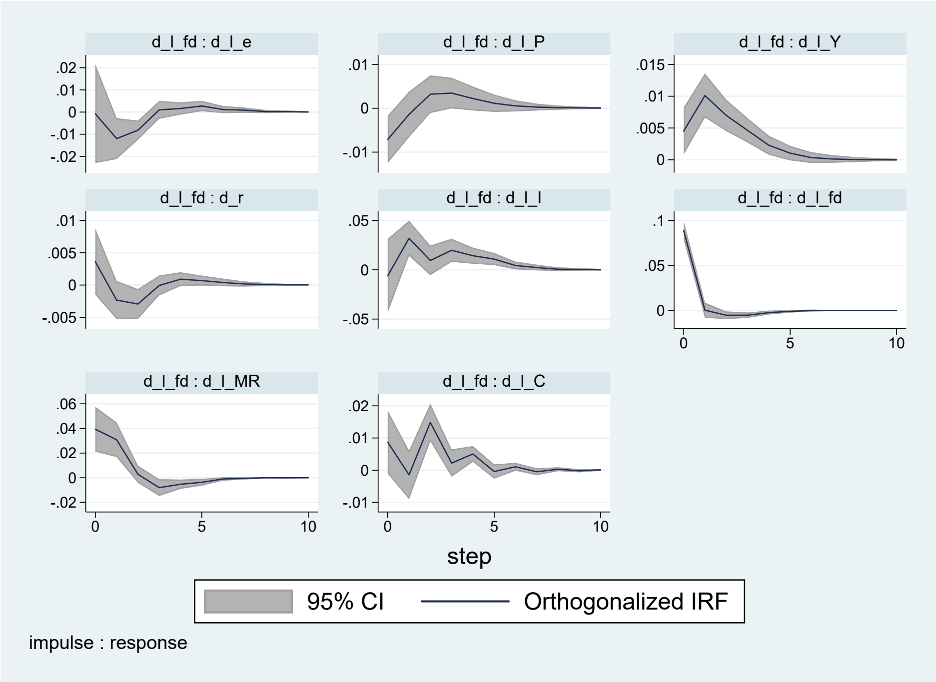


Figure B.38: Cumulative IRF - Impulse on Financial Development, Benchmark, reduced sample, “Low” Financial Development

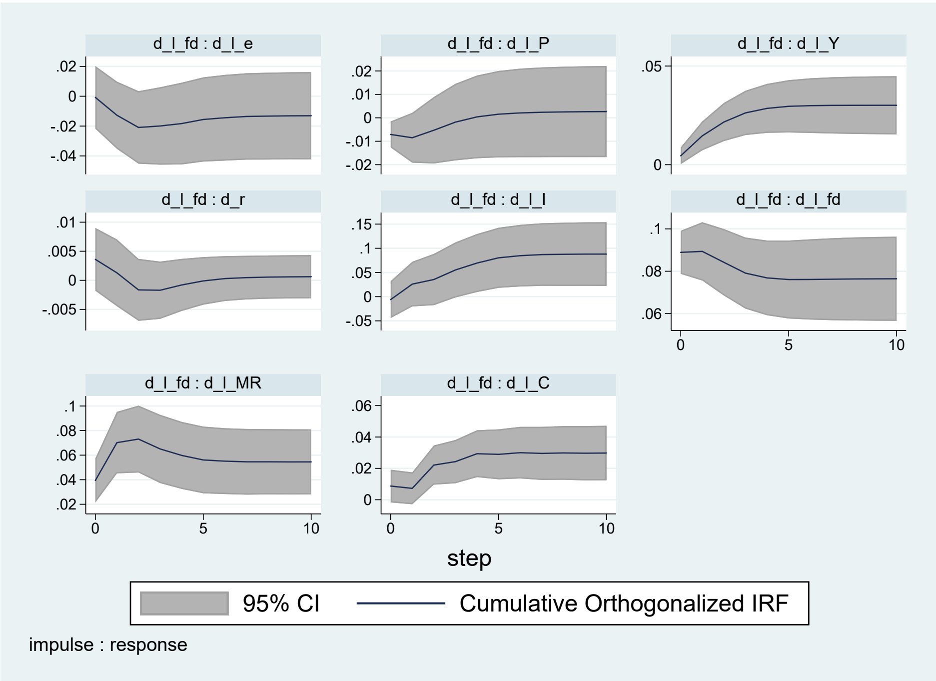


Figure B.39: IRF - Response of Financial Development, Benchmark, reduced sample, "Low" Financial Development

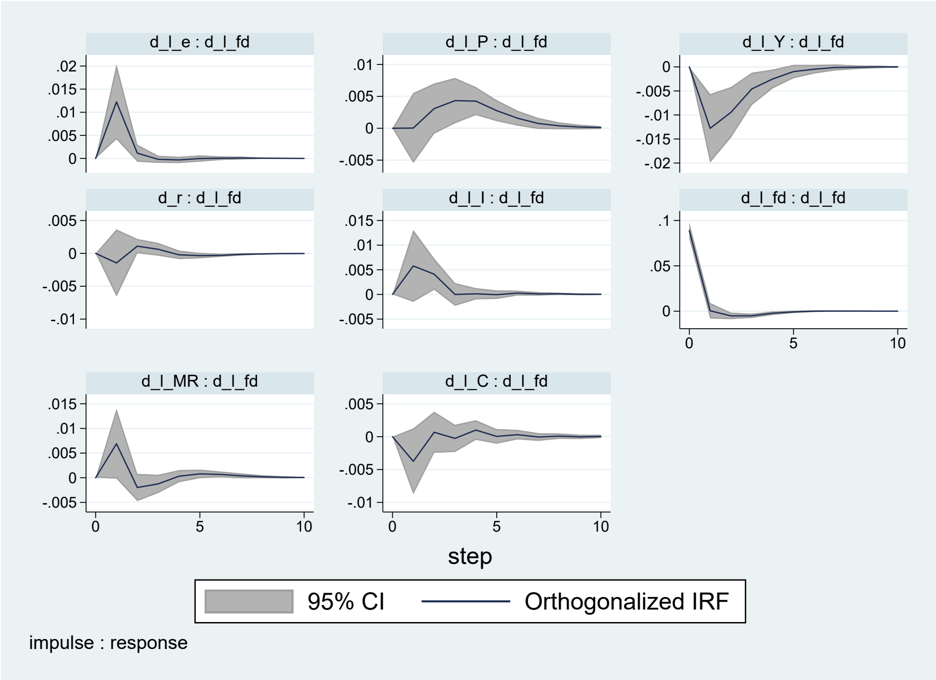
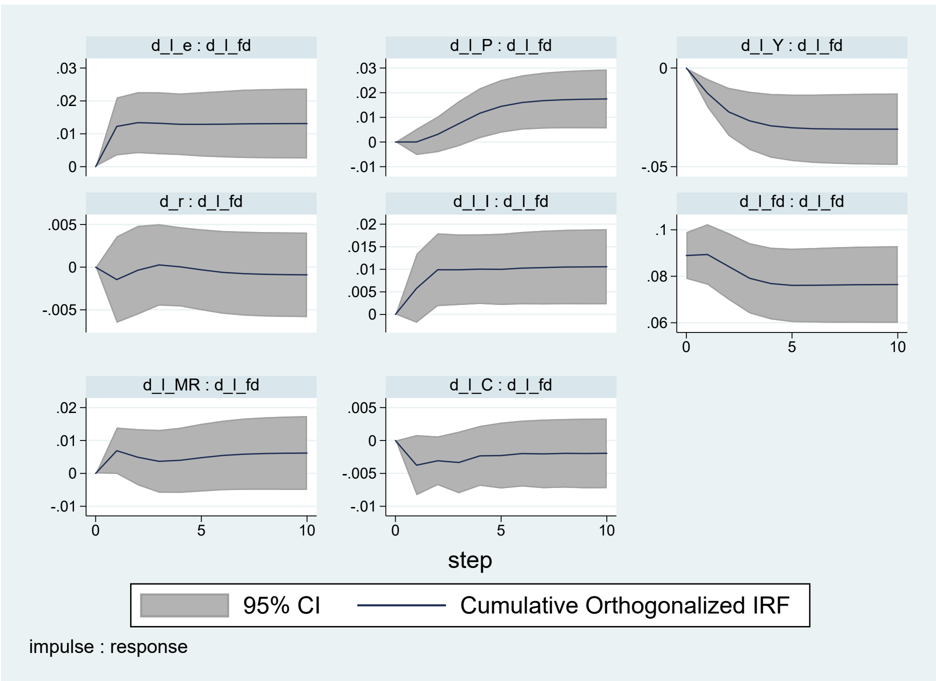


Figure B.40: Cumulative IRF - Response of Financial Development, Benchmark, reduced sample, "Low" Financial Development



B.4.2 Private Credit

Table B.11: Granger causality tests - Private Credit (pcred) as a Financial Development Indicator

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_pcred
d_l_e	NA	0.518	0.222	0.091	0.000	0.001	0.058	0.000
d_r	0.699	NA	0.822	0.000	0.000	0.132	0.099	0.660
d_l_MR	0.698	0.027	NA	0.000	0.143	0.369	0.012	0.373
d_l_P	0.000	0.000	0.000	NA	0.000	0.746	0.034	0.480
d_l_I	0.000	0.917	0.001	0.060	NA	0.000	0.183	0.000
d_l_C	0.000	0.153	0.025	0.649	0.000	NA	0.003	0.111
d_l_Y	0.000	0.043	0.001	0.000	0.000	0.000	NA	0.485
d_l_pcred	0.066	0.292	0.000	0.964	0.822	0.906	0.494	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.41: IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator

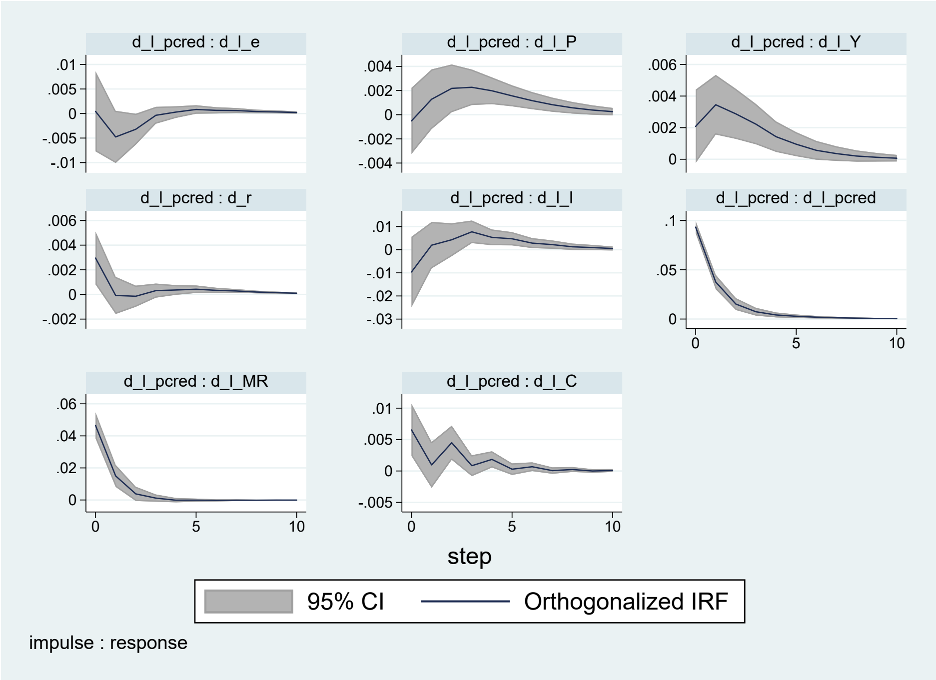


Figure B.42: Cumulative IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator

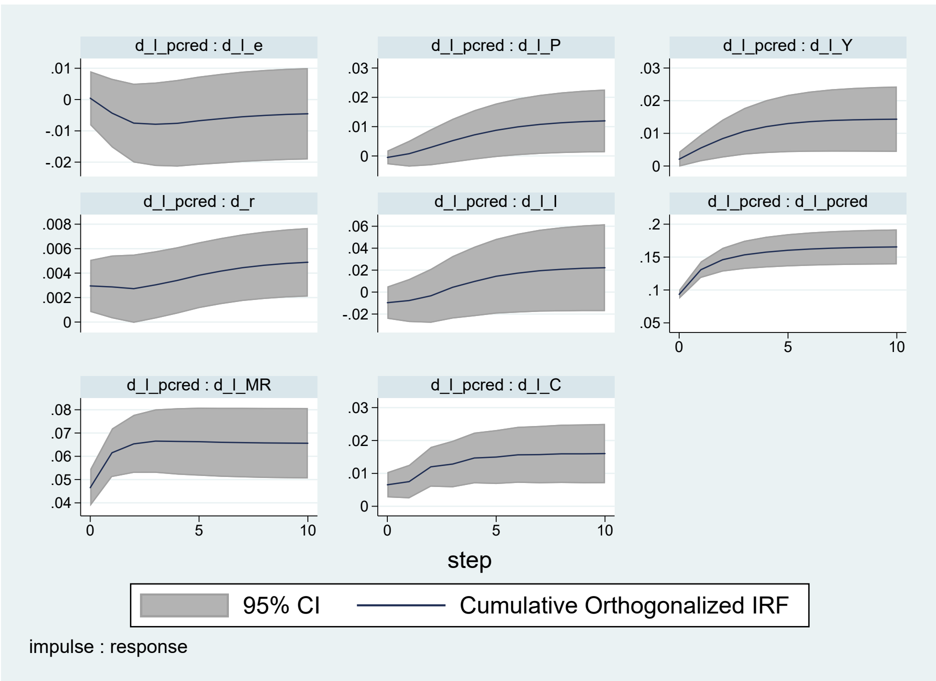


Figure B.43: IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator

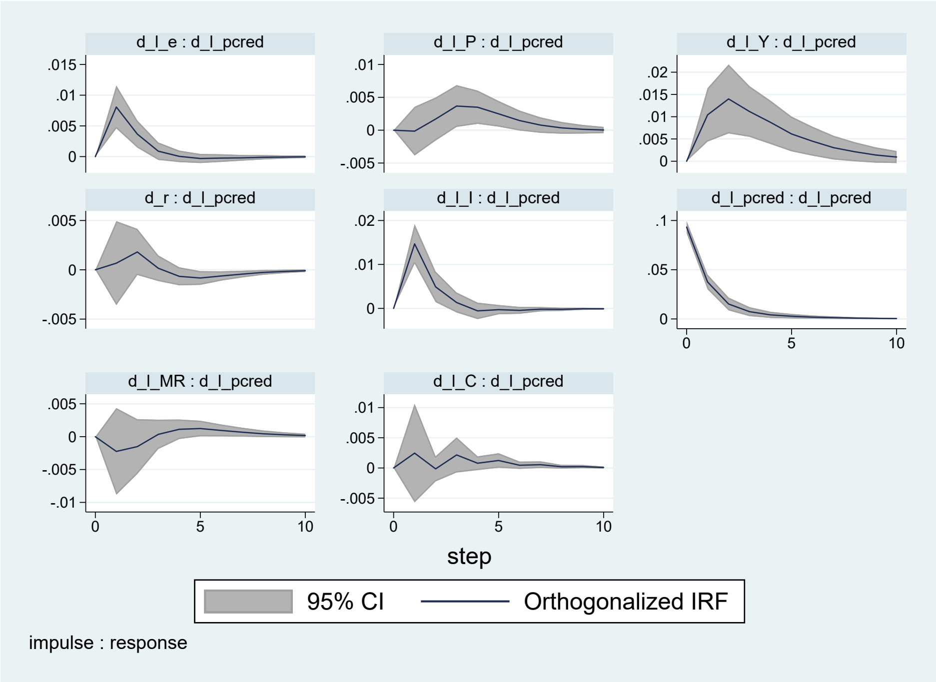


Figure B.44: Cumulative IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator

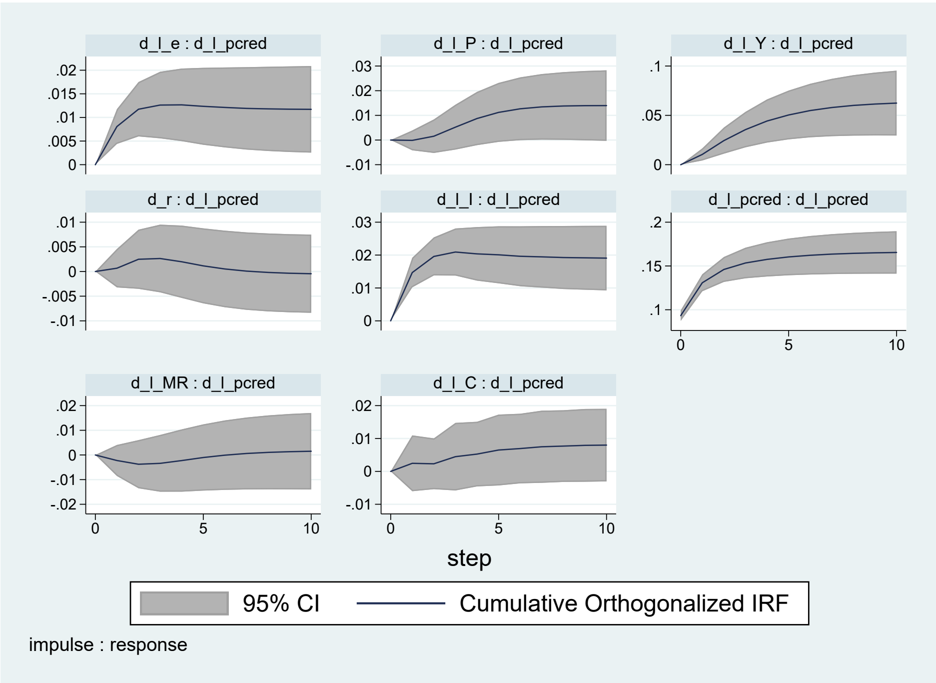


Table B.12: Granger causality tests - Private Credit (pcred) as a Financial Development Indicator, “high” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_pcred
d_l_e	NA	0.050	0.347	0.002	0.008	0.002	0.246	0.074
d_r	0.011	NA	0.096	0.091	0.164	0.992	0.091	0.023
d_l_MR	0.000	0.046	NA	0.034	0.499	0.386	0.180	0.186
d_l_P	0.002	0.000	0.171	NA	0.126	0.326	0.649	0.246
d_l_I	0.174	0.027	0.155	0.257	NA	0.891	0.101	0.379
d_l_C	0.079	0.009	0.039	0.124	0.322	NA	0.000	0.061
d_l_Y	0.015	0.062	0.369	0.318	0.000	0.502	NA	0.379
d_l_pcred	0.262	0.459	0.397	0.393	0.256	0.001	0.030	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.45: IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator, “high” levels

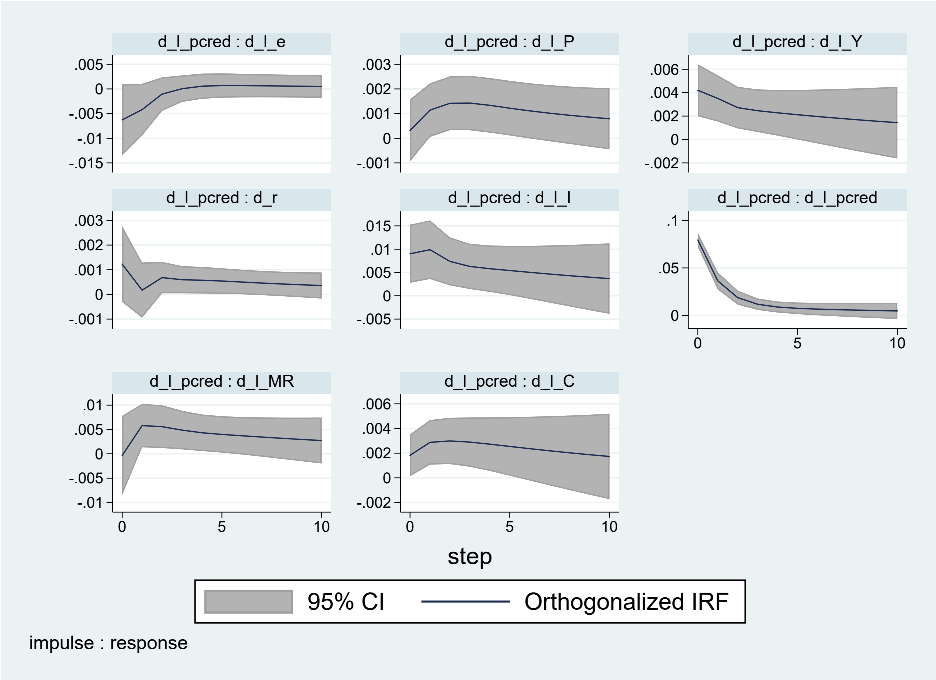


Figure B.46: Cumulative IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator, “high” levels

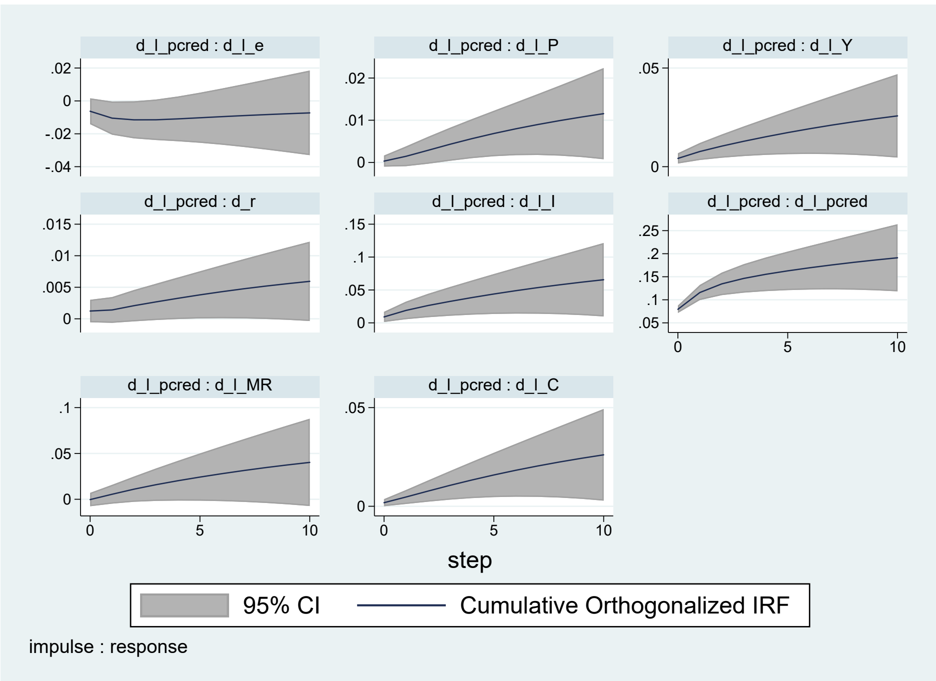


Figure B.47: IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator, “high” levels

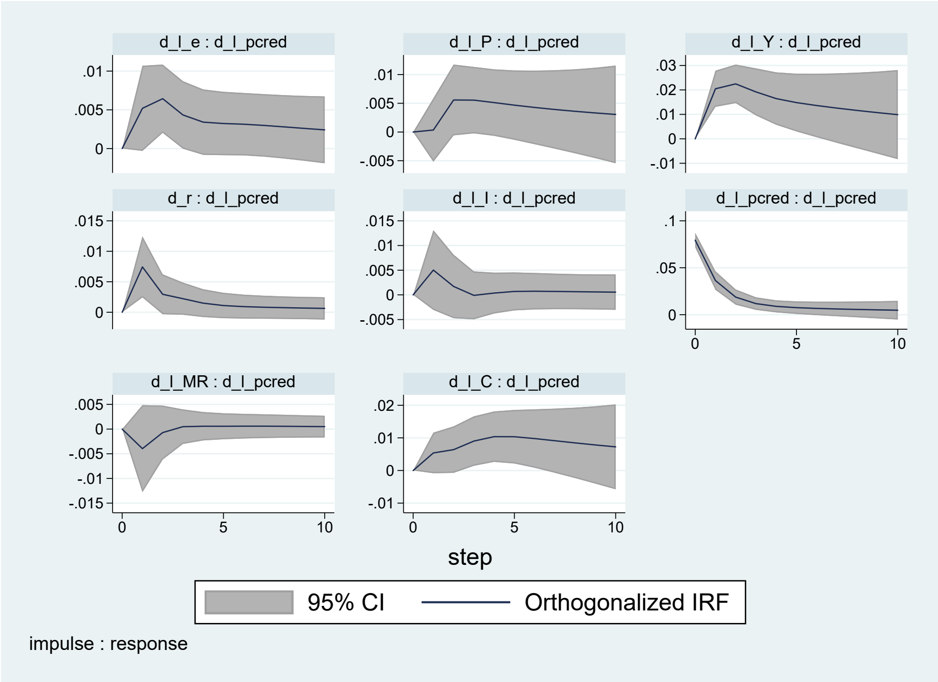


Figure B.48: Cumulative IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator, “high” levels

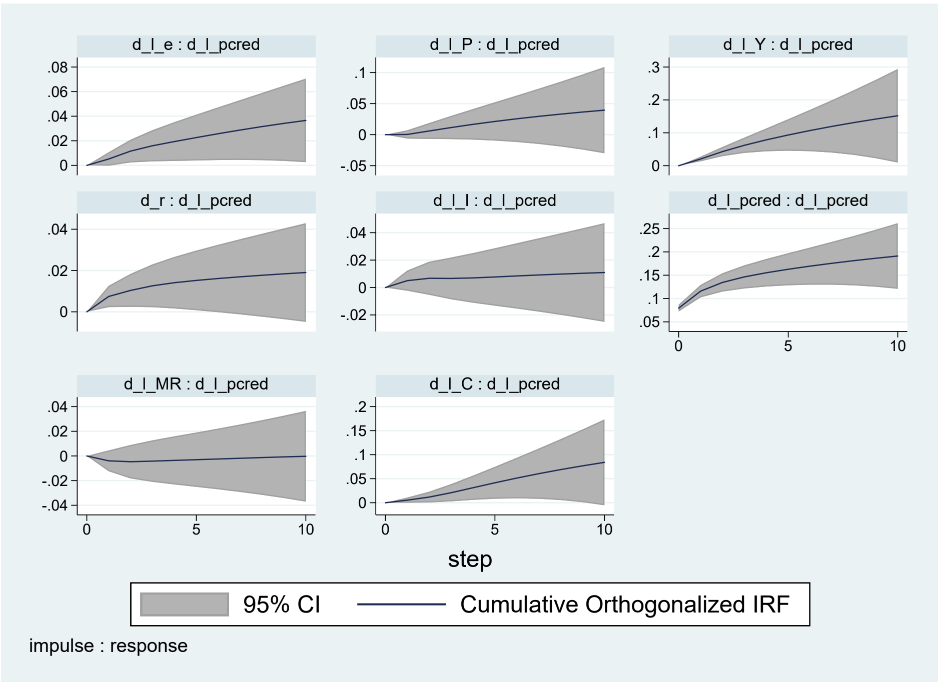


Table B.13: Granger causality tests - Private Credit (pcred) as a Financial Development Indicator, “low” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_pcred
d_l_e	NA	0.380	0.076	0.039	0.000	0.599	0.000	0.000
d_r	0.013	NA	0.355	0.000	0.000	0.003	0.016	0.731
d_l_MR	0.400	0.000	NA	0.000	0.000	0.024	0.002	0.717
d_l_P	0.000	0.000	0.000	NA	0.000	0.201	0.039	0.000
d_l_I	0.000	0.512	0.000	0.322	NA	0.000	0.353	0.000
d_l_C	0.000	0.429	0.108	0.778	0.001	NA	0.006	0.579
d_l_Y	0.000	0.000	0.000	0.000	0.006	0.000	NA	0.270
d_l_pcred	0.033	0.000	0.072	0.002	0.003	0.041	0.801	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.49: IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator, “low” levels

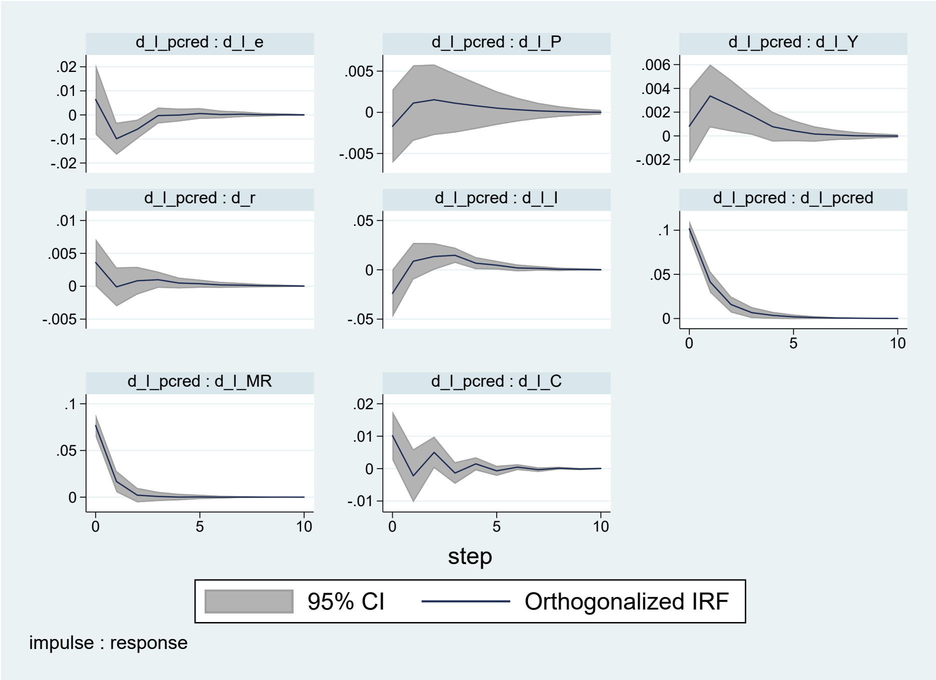


Figure B.50: Cumulative IRF - Impulse on Financial Development, Private Credit (pcred) as a Financial Development Indicator, “low” levels

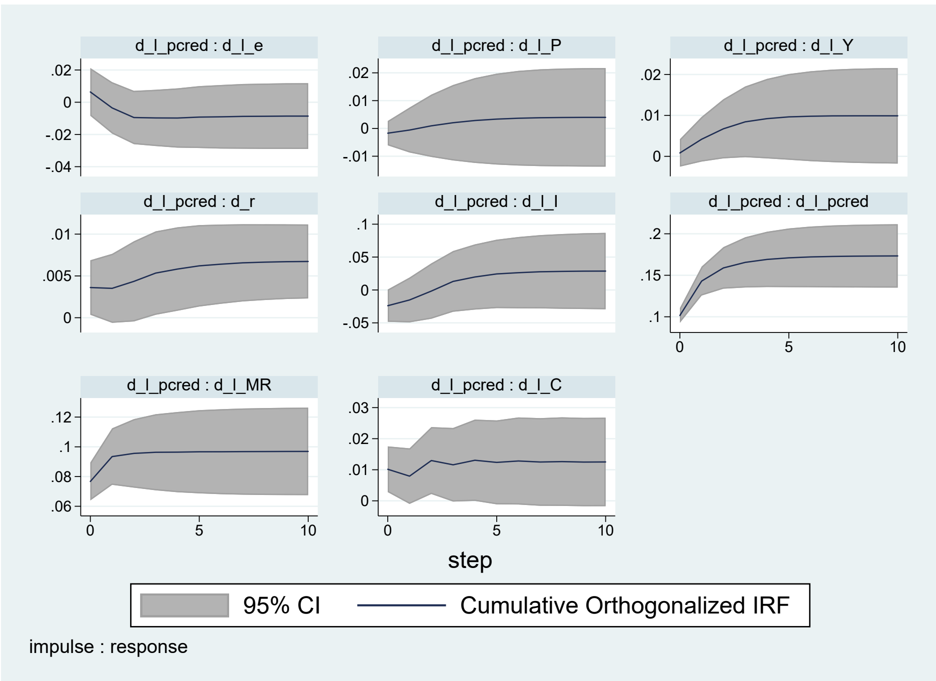


Figure B.51: IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator, “low” levels

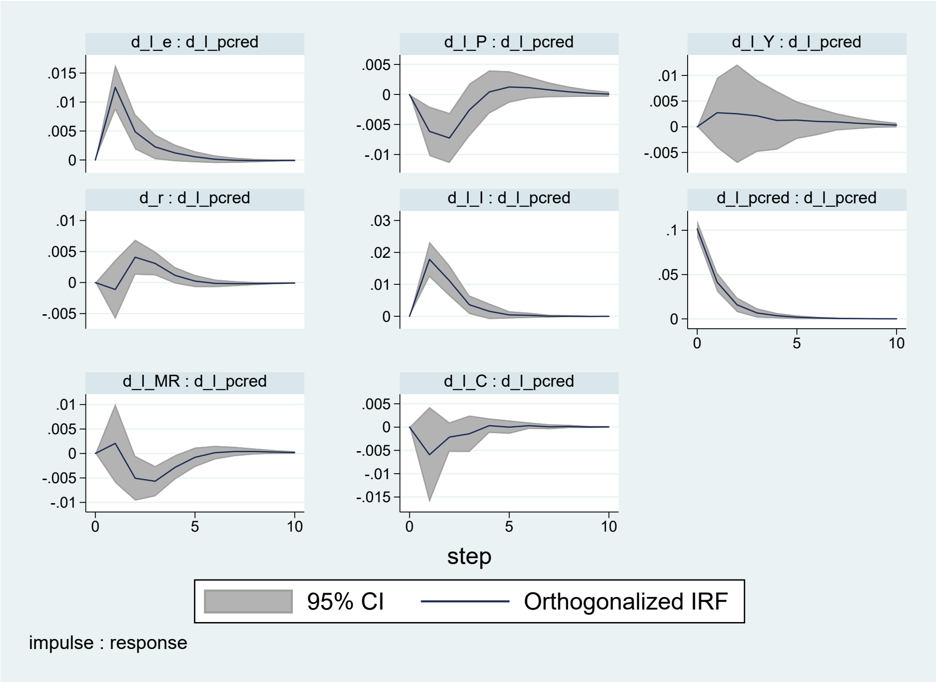
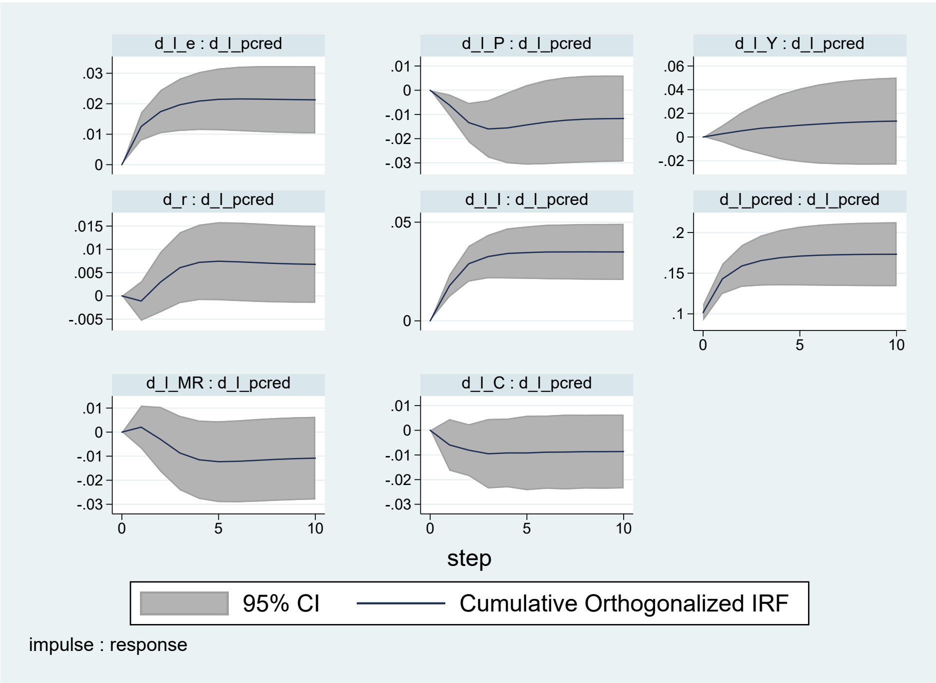


Figure B.52: Cumulative IRF - Response of Financial Development, Private Credit (pcred) as a Financial Development Indicator, “low” levels



B.4.3 Stock Market Capitalization

Table B.14: Granger causality tests - Stock Market Capitalization (smcap) as a Financial Development Indicator

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smcap
d_l_e	NA	0.698	0.382	0.146	0.000	0.000	0.043	0.371
d_r	0.237	NA	0.252	0.000	0.008	0.004	0.002	0.608
d_l_MR	0.766	0.000	NA	0.000	0.003	0.096	0.335	0.001
d_l_P	0.000	0.000	0.000	NA	0.000	0.225	0.000	0.038
d_l_I	0.000	0.006	0.050	0.007	NA	0.000	0.393	0.020
d_l_C	0.000	0.140	0.444	0.635	0.000	NA	0.000	0.189
d_l_Y	0.000	0.913	0.392	0.000	0.000	0.000	NA	0.000
d_l_smcap	0.000	0.010	0.499	0.961	0.000	0.169	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.53: IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator

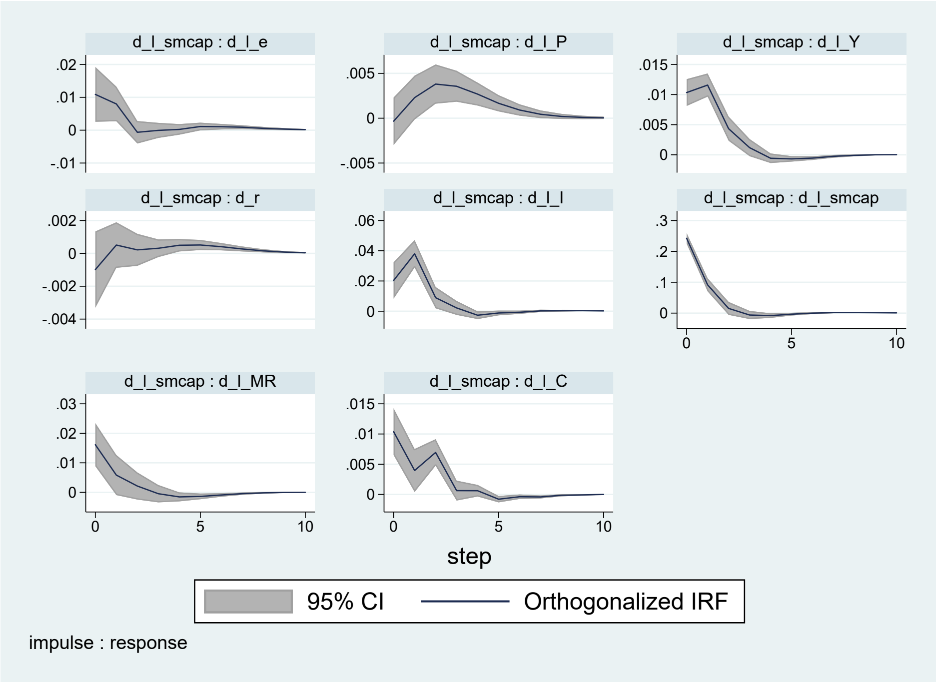


Figure B.54: Cumulative IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator

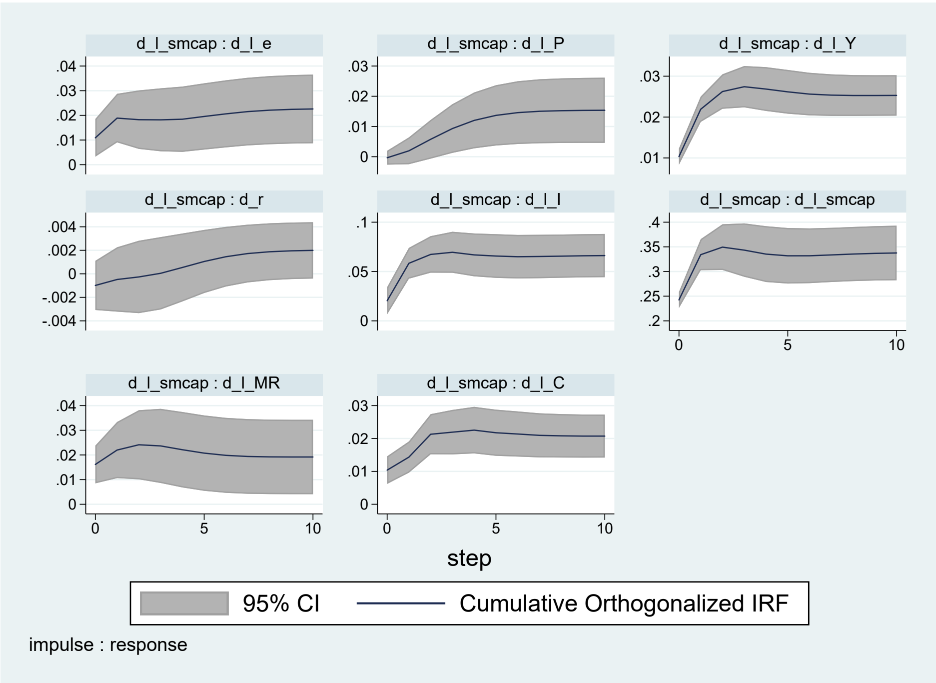


Figure B.55: IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator

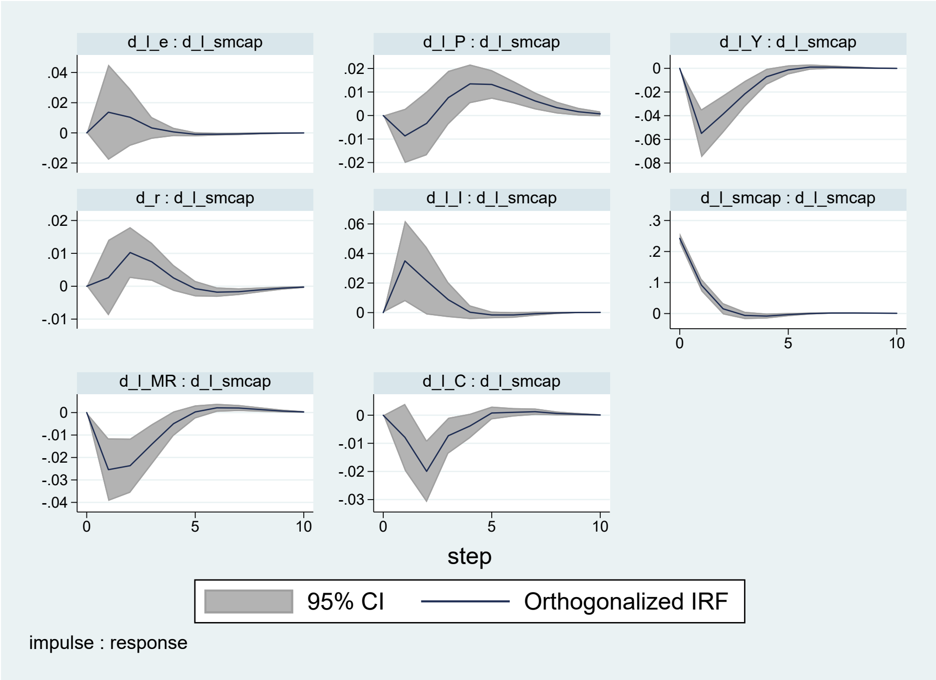


Figure B.56: Cumulative IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator

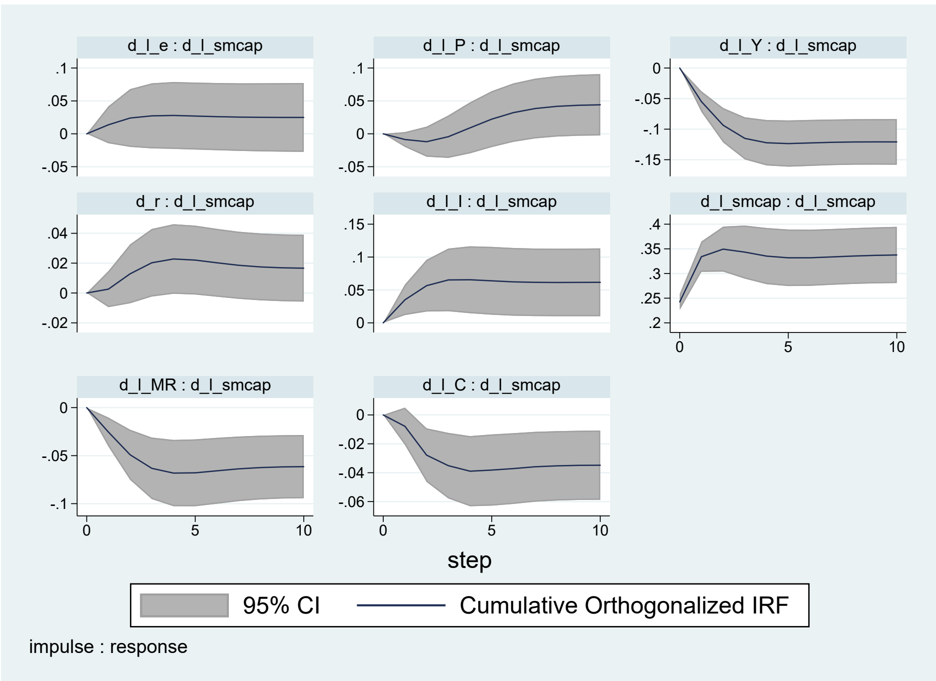


Table B.15: Granger causality tests - Stock Market Capitalization (smcap) as a Financial Development Indicator, “high” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smcap
d_l_e	NA	0.046	0.966	0.031	0.522	0.184	0.001	0.000
d_r	0.110	NA	0.000	0.307	0.093	0.001	0.000	0.019
d_l_MR	0.224	0.004	NA	0.632	0.356	0.097	0.091	0.047
d_l_P	0.003	0.000	0.000	NA	0.000	0.000	0.000	0.000
d_l_I	0.208	0.006	0.282	0.547	NA	0.263	0.099	0.067
d_l_C	0.000	0.001	0.007	0.006	0.337	NA	0.938	0.678
d_l_Y	0.550	0.001	0.743	0.423	0.423	0.000	NA	0.000
d_l_smcap	0.272	0.717	0.418	0.000	0.000	0.000	0.000	NA
ALL	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.57: IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “high” levels

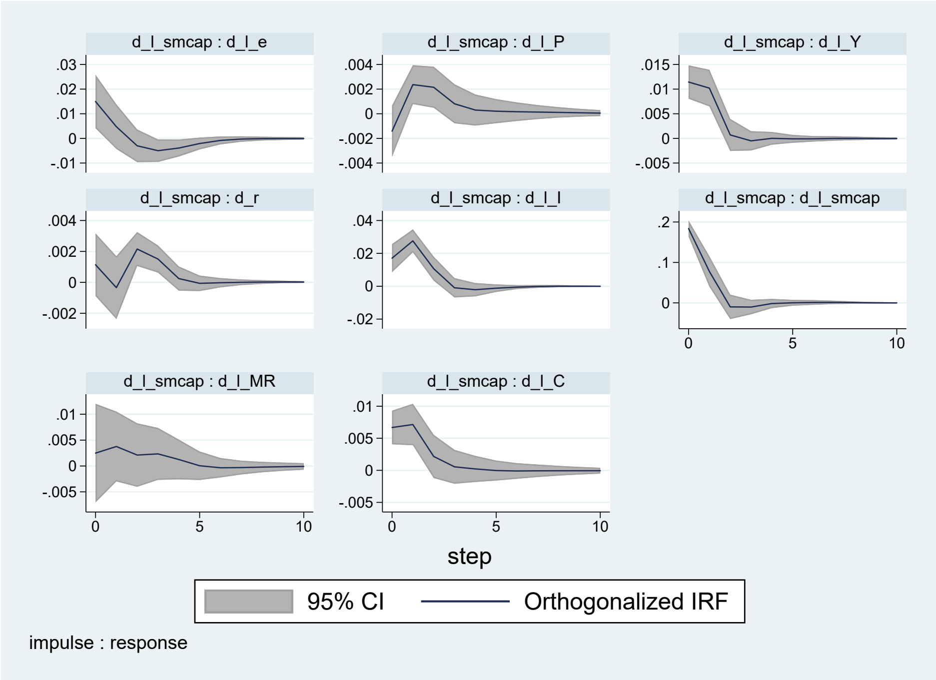


Figure B.58: Cumulative IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “high” levels

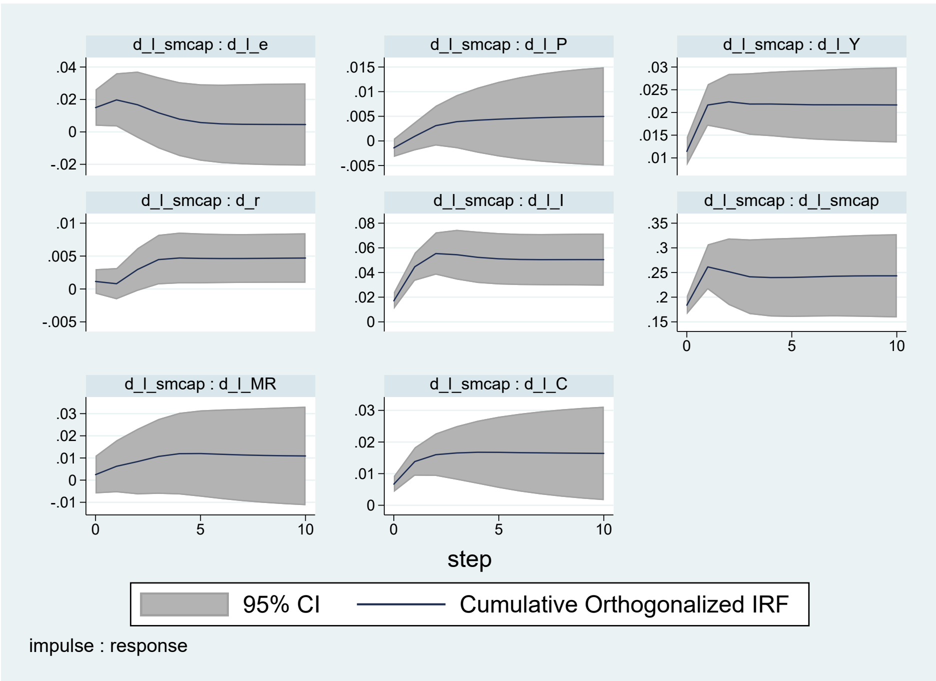


Figure B.59: IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “high” levels

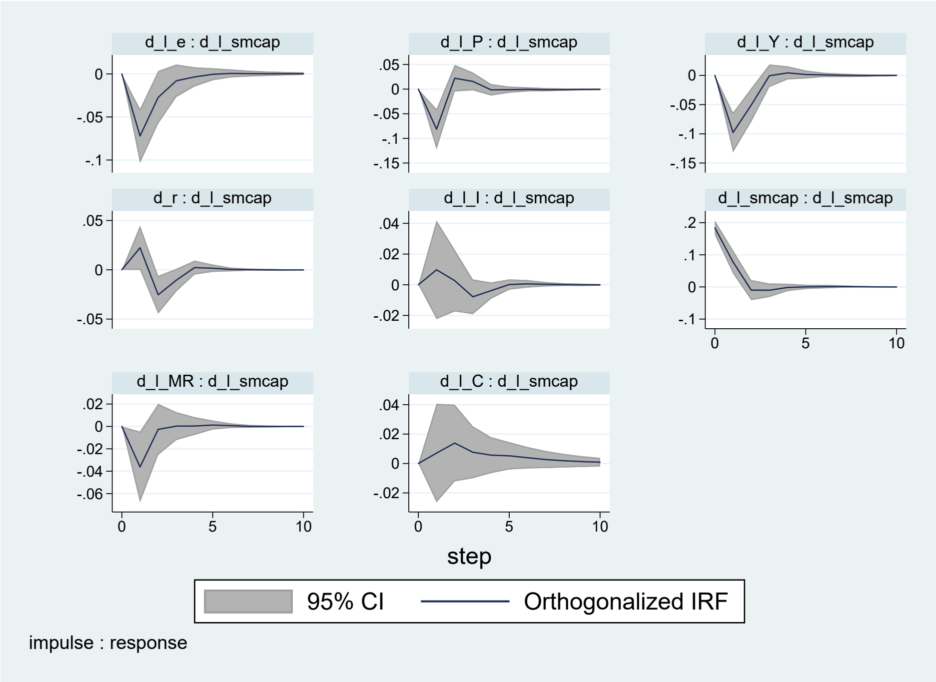


Figure B.60: Cumulative IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “high” levels

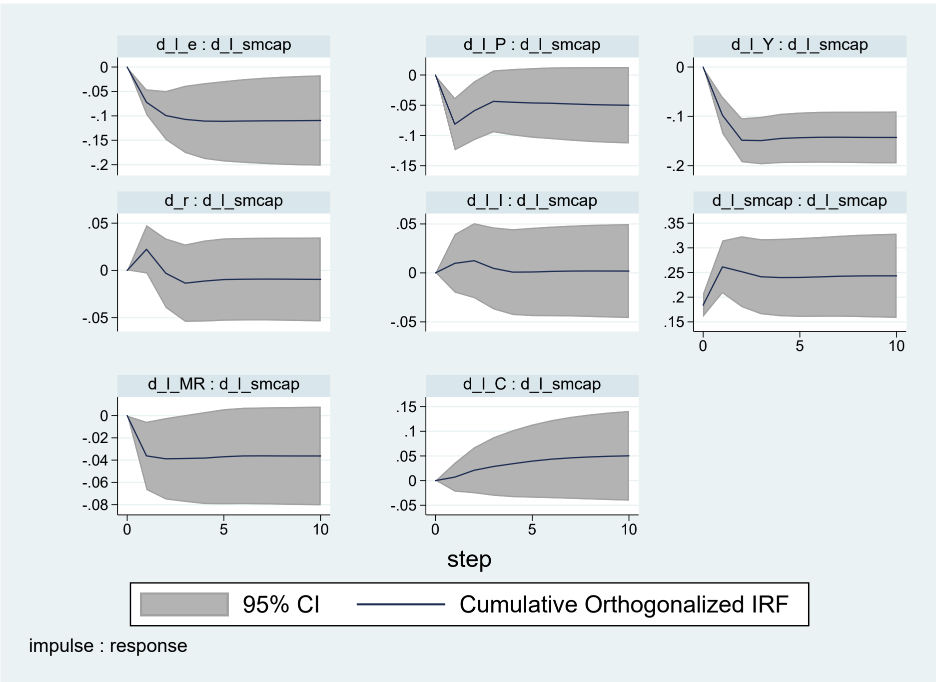


Table B.16: Granger causality tests - Stock Market Capitalization (smcap) as a Financial Development Indicator, “low” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smcap
d_l_e	NA	0.283	0.896	0.000	0.002	0.040	0.000	0.333
d_r	0.529	NA	0.429	0.000	0.000	0.019	0.000	0.063
d_l_MR	0.320	0.000	NA	0.000	0.000	0.351	0.360	0.000
d_l_P	0.000	0.000	0.000	NA	0.161	0.492	0.000	0.535
d_l_I	0.000	0.000	0.166	0.000	NA	0.000	0.003	0.002
d_l_C	0.000	0.000	0.336	0.234	0.026	NA	0.000	0.008
d_l_Y	0.000	0.504	0.547	0.000	0.000	0.000	NA	0.000
d_l_smcap	0.000	0.000	0.010	0.003	0.000	0.000	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.61: IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “low” levels

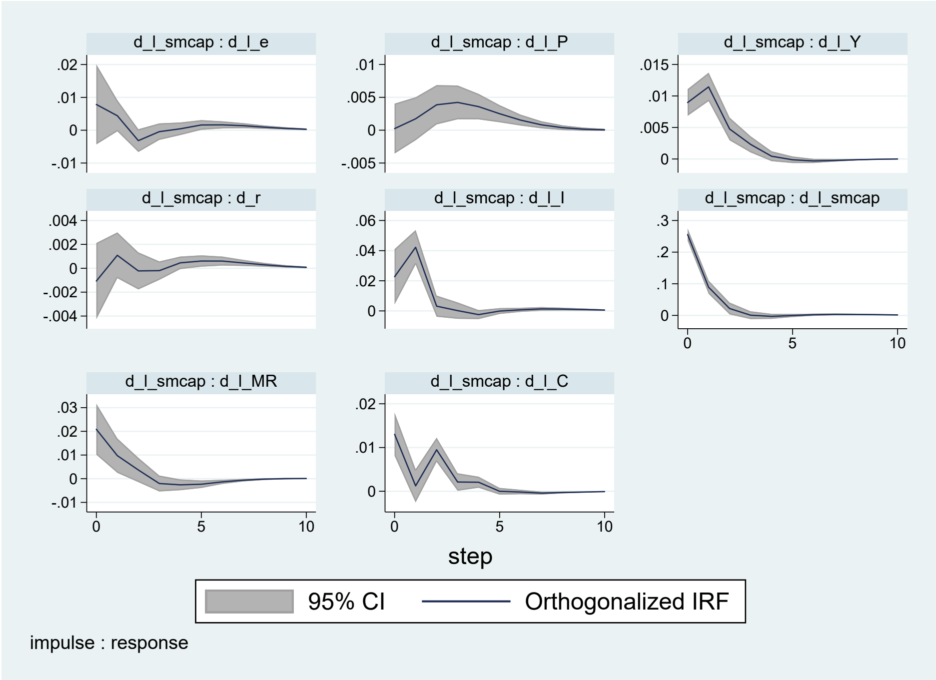


Figure B.62: Cumulative IRF - Impulse on Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, “low” levels

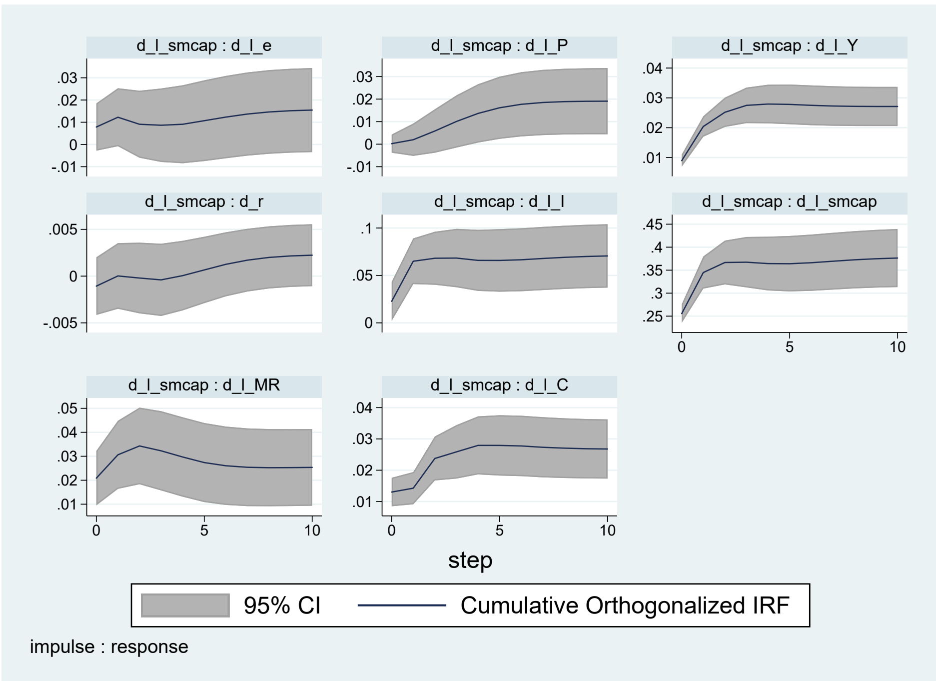


Figure B.63: IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, "low" levels

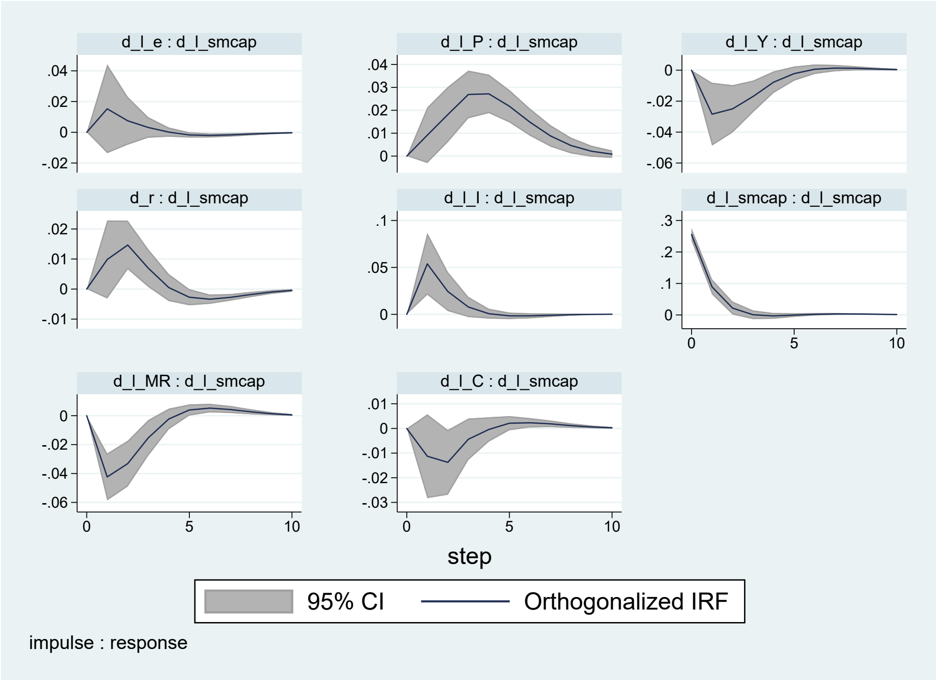
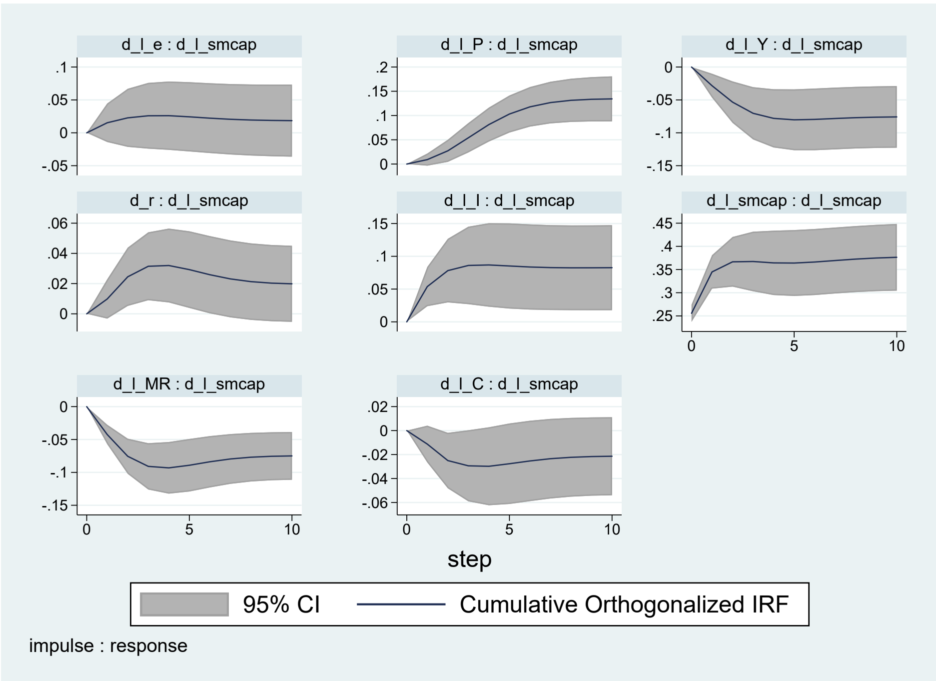


Figure B.64: Cumulative IRF - Response of Financial Development, Stock Market Capitalization (smcap) as a Financial Development Indicator, "low" levels



B.4.4 Stock Market Total Value Traded

Table B.17: Granger causality tests - Stock Market Total Value Traded (smt) as a Financial Development Indicator

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smt
d_l_e	NA	0.430	0.136	0.061	0.000	0.005	0.312	0.573
d_r	0.007	NA	0.658	0.000	0.001	0.746	0.701	0.000
d_l_MR	0.077	0.021	NA	0.000	0.351	0.363	0.170	0.000
d_l_P	0.047	0.000	0.000	NA	0.000	0.019	0.001	0.000
d_l_I	0.000	0.665	0.001	0.010	NA	0.000	0.026	0.039
d_l_C	0.000	0.207	0.032	0.783	0.002	NA	0.000	0.000
d_l_Y	0.001	0.013	0.012	0.000	0.000	0.000	NA	0.000
d_l_smt	0.300	0.906	0.024	0.133	0.964	0.025	0.792	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.65: IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator

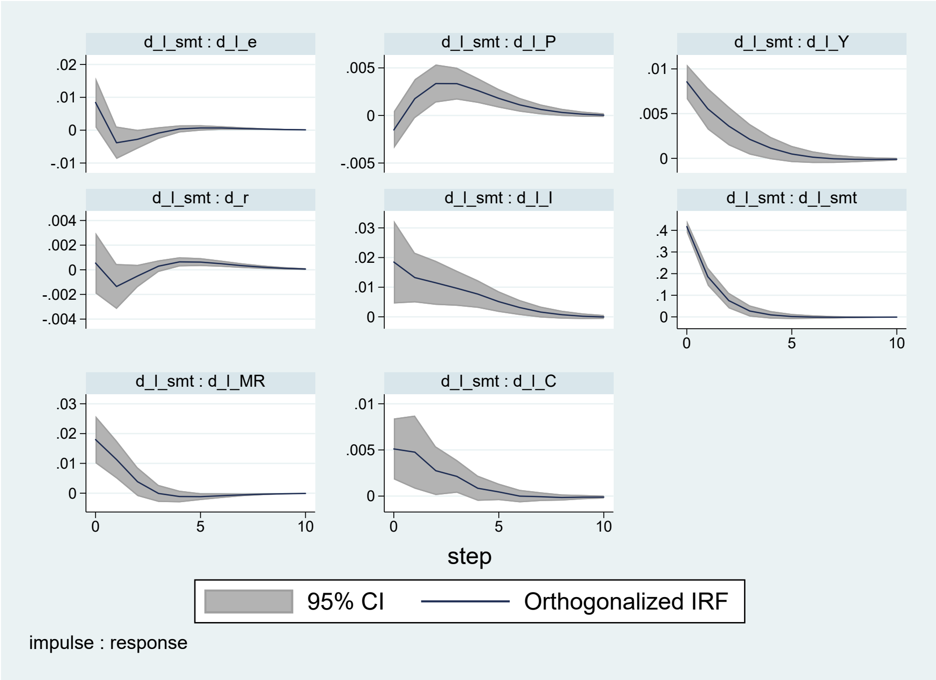


Figure B.66: Cumulative IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator

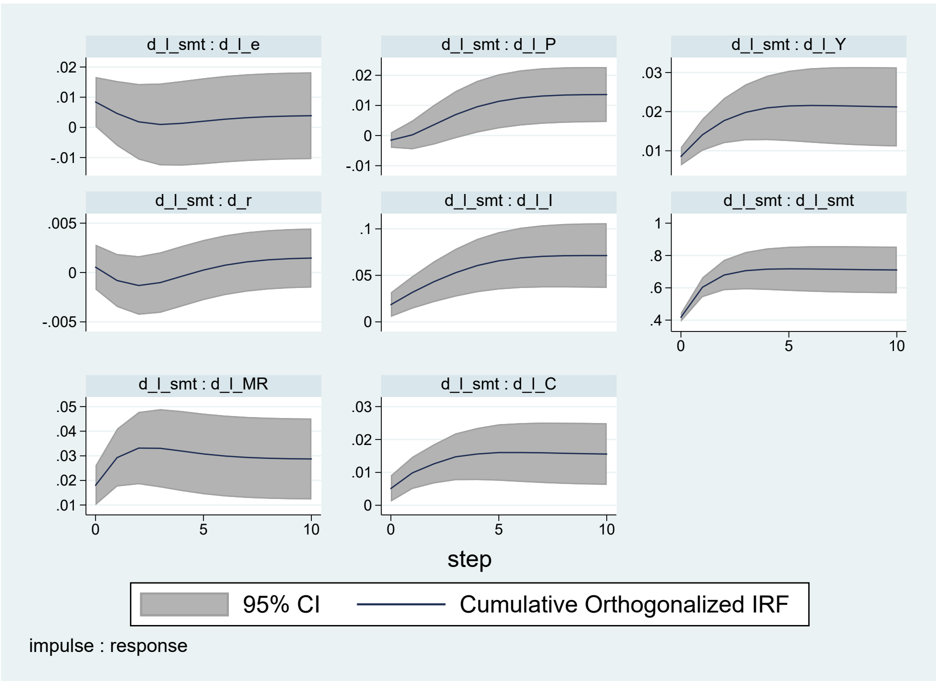


Figure B.67: IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator

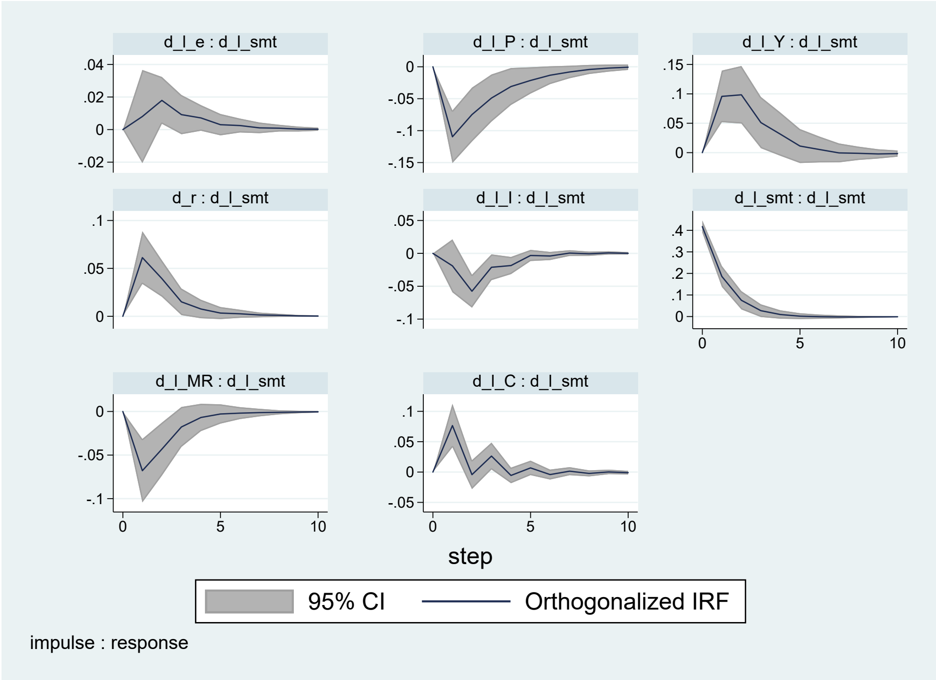


Figure B.68: Cumulative IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator

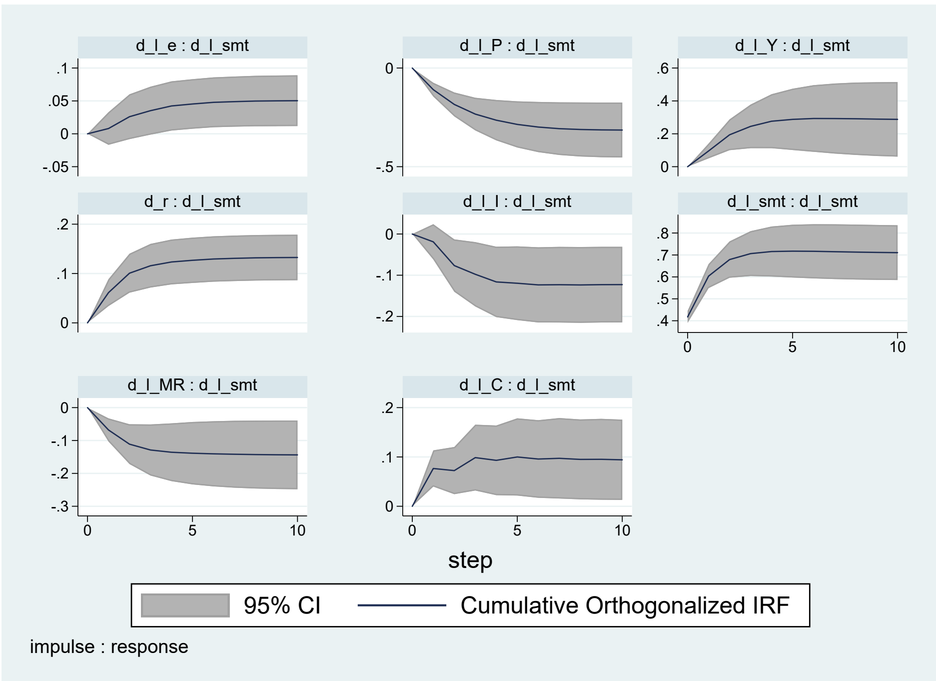


Table B.18: Granger causality tests - Stock Market Total Value Traded (smt) as a Financial Development Indicator, “high” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smt
d_l_e	NA	0.147	0.248	0.953	0.002	0.266	0.073	0.106
d_r	0.260	NA	0.286	0.000	0.014	0.019	0.000	0.001
d_l_MR	0.173	0.078	NA	0.438	0.936	0.885	0.743	0.681
d_l_P	0.875	0.000	0.650	NA	0.617	0.337	0.366	0.610
d_l_I	0.001	0.004	0.005	0.000	NA	0.388	0.000	0.000
d_l_C	0.000	0.137	0.203	0.000	0.000	NA	0.002	0.000
d_l_Y	0.000	0.105	0.328	0.000	0.000	0.152	NA	0.000
d_l_smt	0.278	0.044	0.192	0.550	0.320	0.924	0.410	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.037	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.69: IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “high” levels

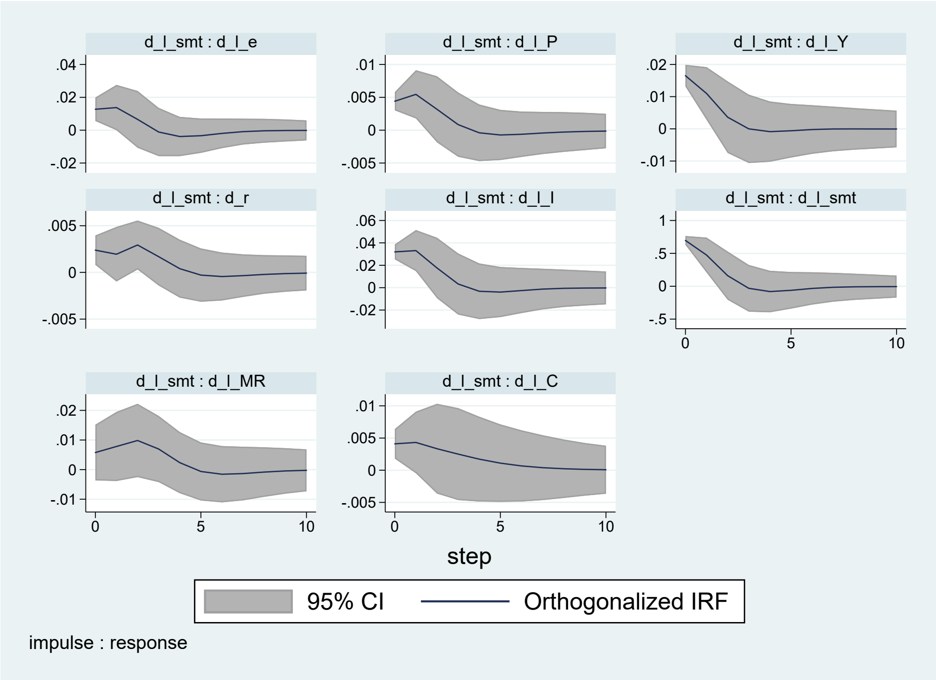


Figure B.70: Cumulative IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “high” levels

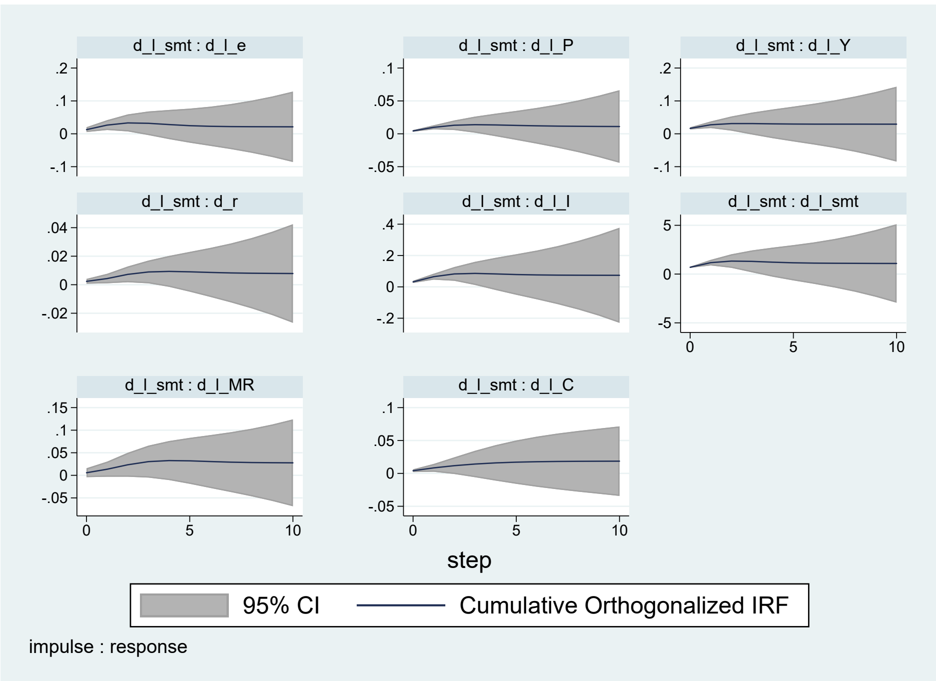


Figure B.71: IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “high” levels

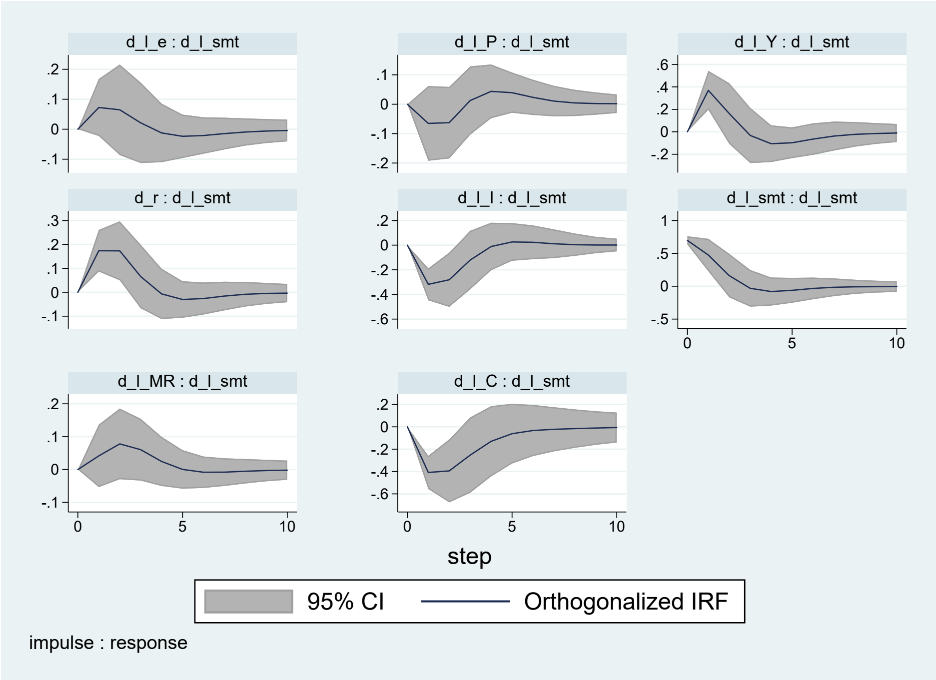


Figure B.72: Cumulative IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “high” levels

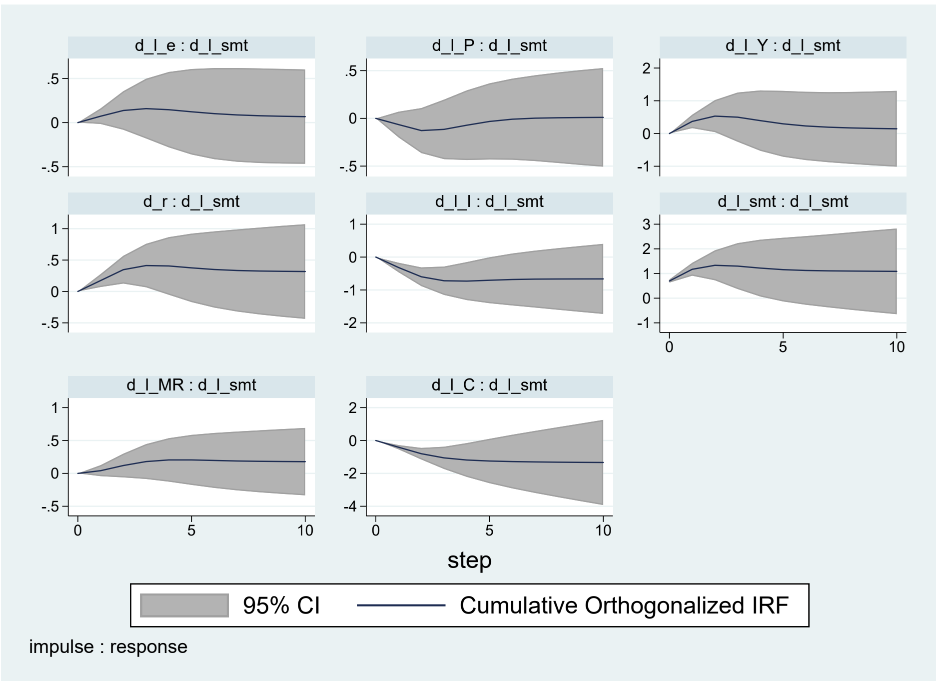


Table B.19: Granger causality tests - Stock Market Total Value Traded (smt) as a Financial Development Indicator, “low” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_smt
d_l_e	NA	0.213	0.157	0.005	0.000	0.005	0.432	0.000
d_r	0.001	NA	0.193	0.000	0.001	0.007	0.006	0.535
d_l_MR	0.000	0.000	NA	0.000	0.001	0.800	0.027	0.000
d_l_P	0.000	0.000	0.000	NA	0.000	0.069	0.007	0.000
d_l_I	0.000	0.107	0.099	0.008	NA	0.000	0.997	0.063
d_l_C	0.000	0.448	0.081	0.076	0.003	NA	0.000	0.000
d_l_Y	0.000	0.078	0.000	0.000	0.000	0.000	NA	0.001
d_l_smt	0.617	0.305	0.000	0.361	0.023	0.000	0.179	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.73: IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “low” levels

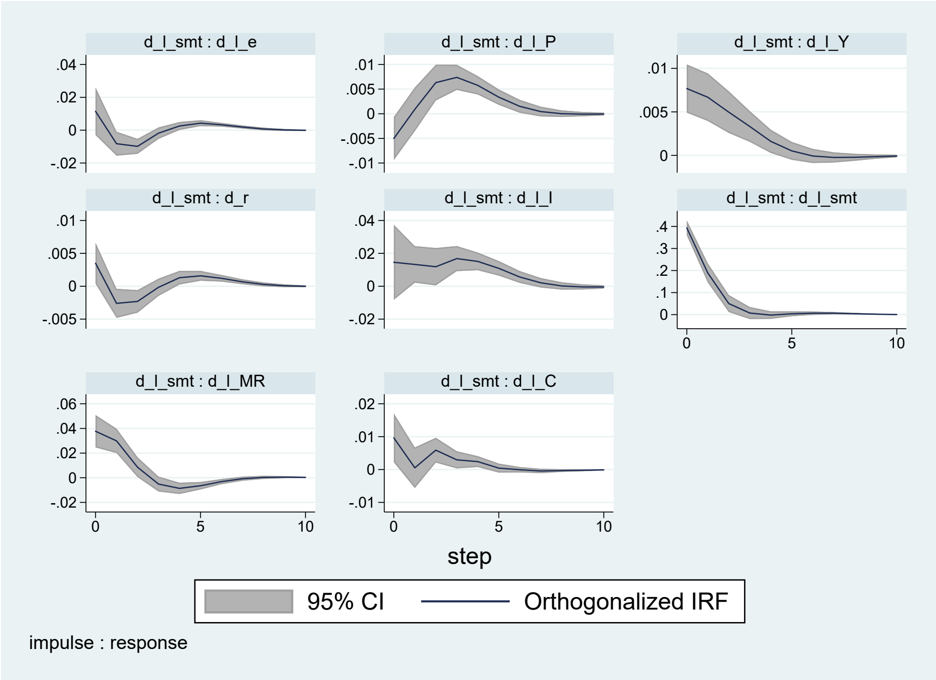


Figure B.74: Cumulative IRF - Impulse on Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, “low” levels

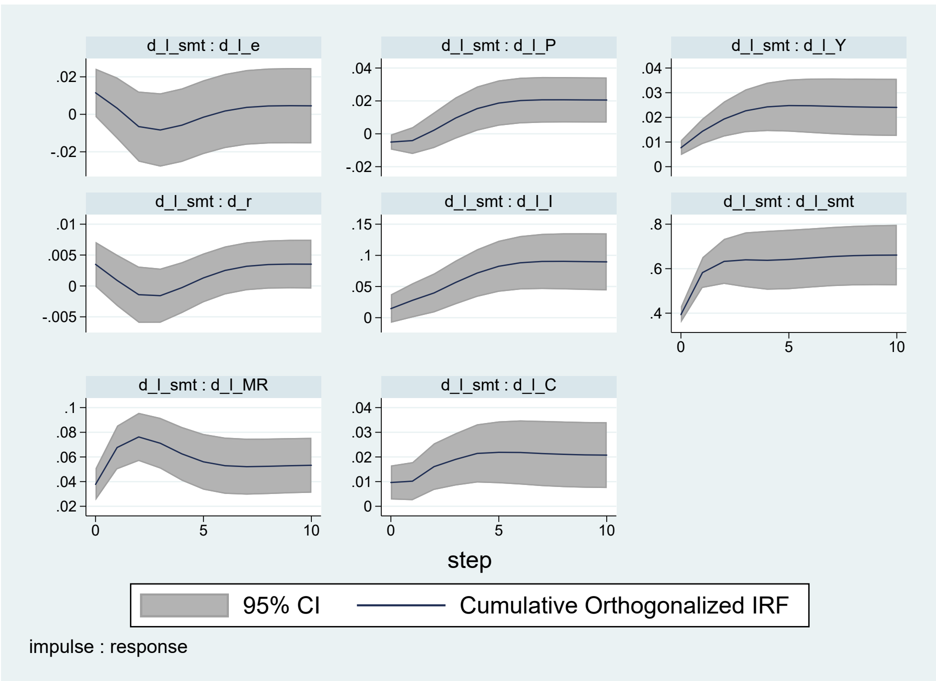


Figure B.75: IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, "low" levels

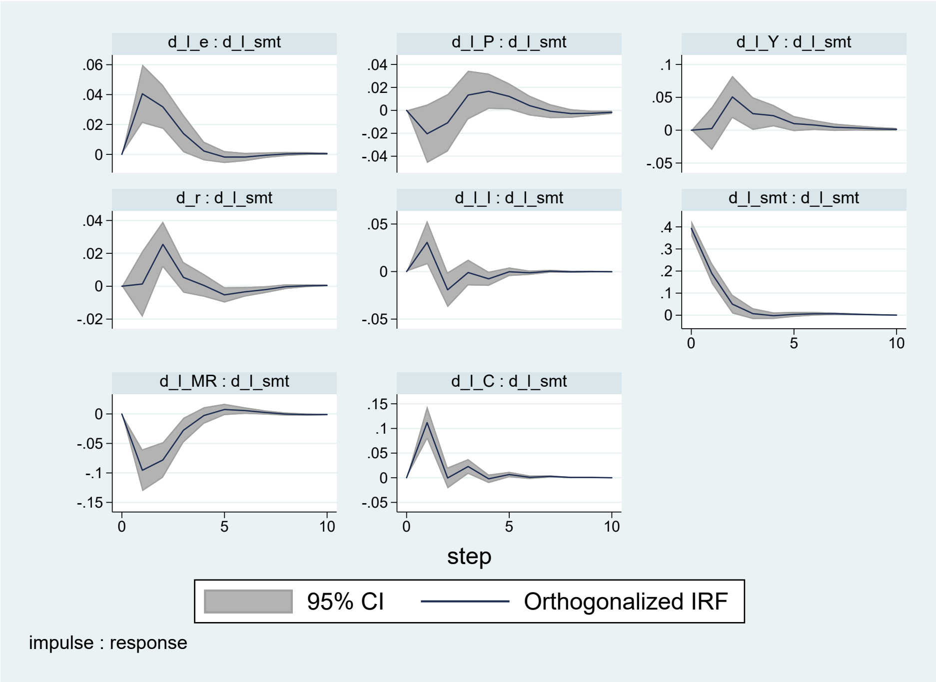
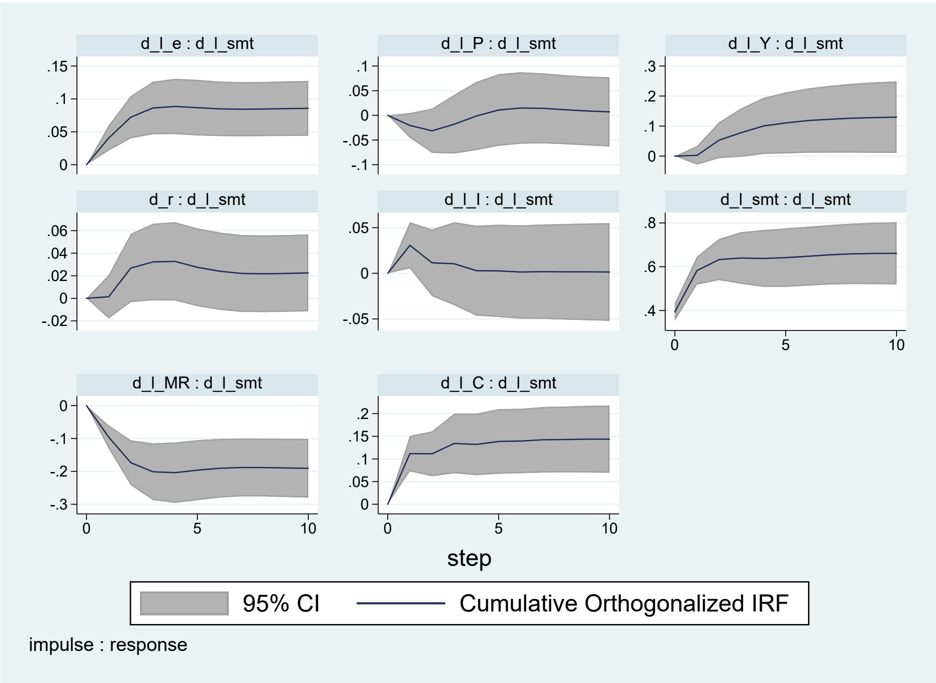


Figure B.76: Cumulative IRF - Response of Financial Development, Stock Market Total Value Traded (smt) as a Financial Development Indicator, "low" levels



B.5 Financial Institution Development

Table B.20: Granger causality tests - Financial Institution Development (fi)

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fi
d_l_e	NA	0.000	0.184	0.000	0.070	0.007	0.056	0.000
d_r	0.021	NA	0.000	0.000	0.501	0.850	0.491	0.007
d_l_MR	0.019	0.165	NA	0.072	0.285	0.885	0.418	0.957
d_l_P	0.049	0.000	0.000	NA	0.016	0.799	0.109	0.000
d_l_I	0.019	0.250	0.608	0.360	NA	0.353	0.494	0.464
d_l_C	0.440	0.414	0.149	0.360	0.099	NA	0.238	0.289
d_l_Y	0.469	0.437	0.028	0.408	0.000	0.000	NA	0.292
d_l_fi	0.604	0.580	0.111	0.020	0.009	0.744	0.323	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.77: IRF - Impulse on Financial Development, Financial Institution Development (fi)

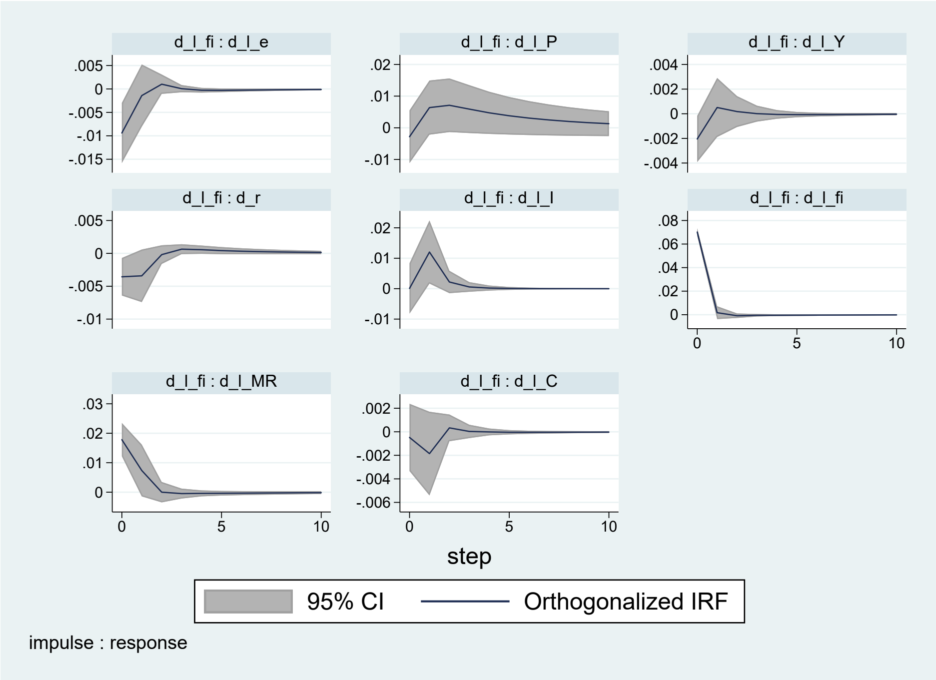


Figure B.78: Cumulative IRF - Impulse on Financial Development, Financial Institution Development (fi)

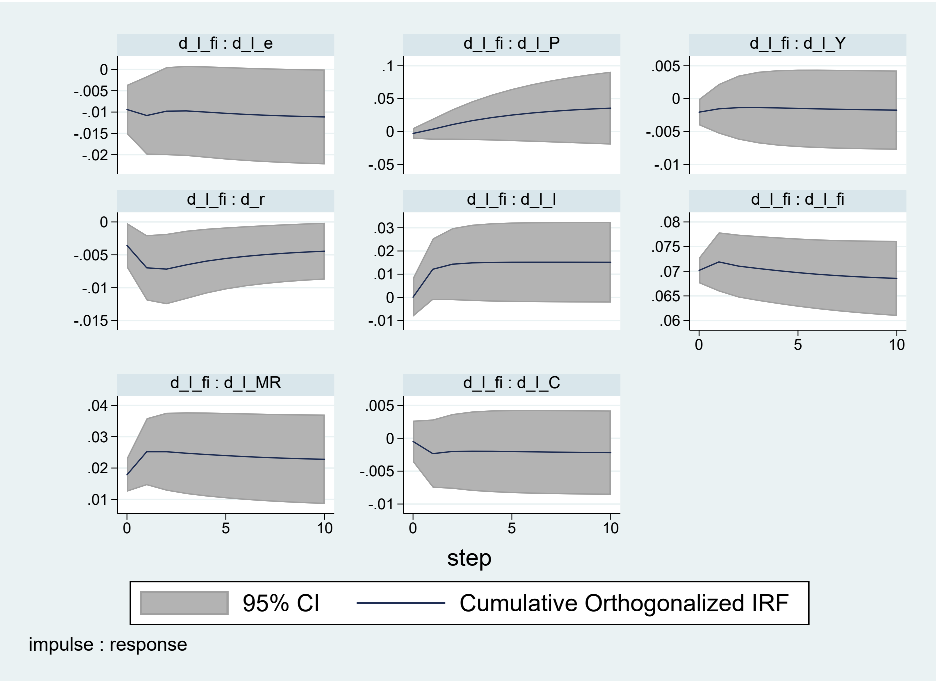


Figure B.79: IRF - Response of Financial Development, Financial Institution Development (fi)

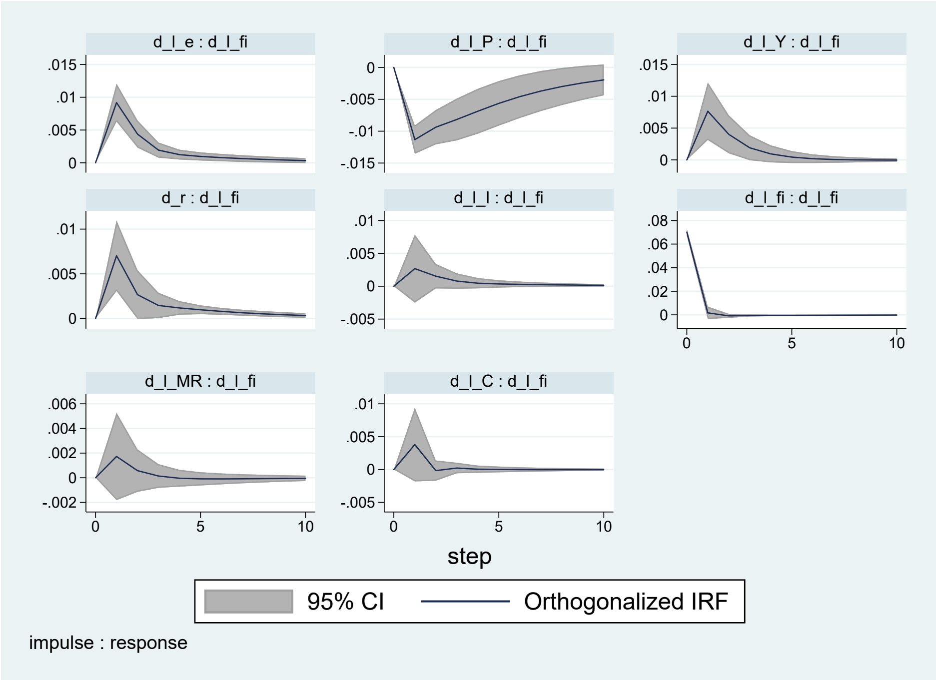


Figure B.80: Cumulative IRF - Response of Financial Development, Financial Institution Development (fi)

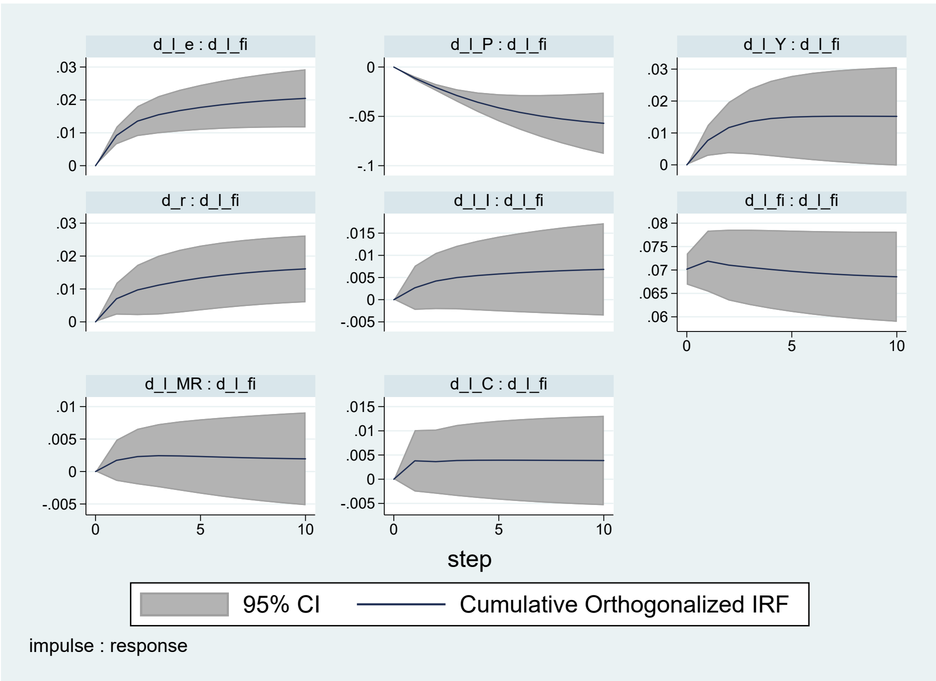


Table B.21: Granger causality tests - Financial Institution Development (fi), "high" levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fi
d_l_e	NA	0.020	0.065	0.000	0.011	0.000	0.933	0.133
d_r	0.049	NA	0.352	0.000	0.242	0.982	0.751	0.172
d_l_MR	0.940	0.587	NA	0.540	0.345	0.783	0.989	0.526
d_l_P	0.388	0.000	0.026	NA	0.410	0.648	0.645	0.581
d_l_I	0.344	0.000	0.001	0.621	NA	0.898	0.185	0.002
d_l_C	0.000	0.000	0.201	0.000	0.948	NA	0.055	0.010
d_l_Y	0.000	0.506	0.077	0.239	0.000	0.001	NA	0.714
d_l_fi	0.664	0.579	0.949	0.522	0.000	0.053	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.81: IRF - Impulse on Financial Development, Financial Institution Development (fi), "high" levels

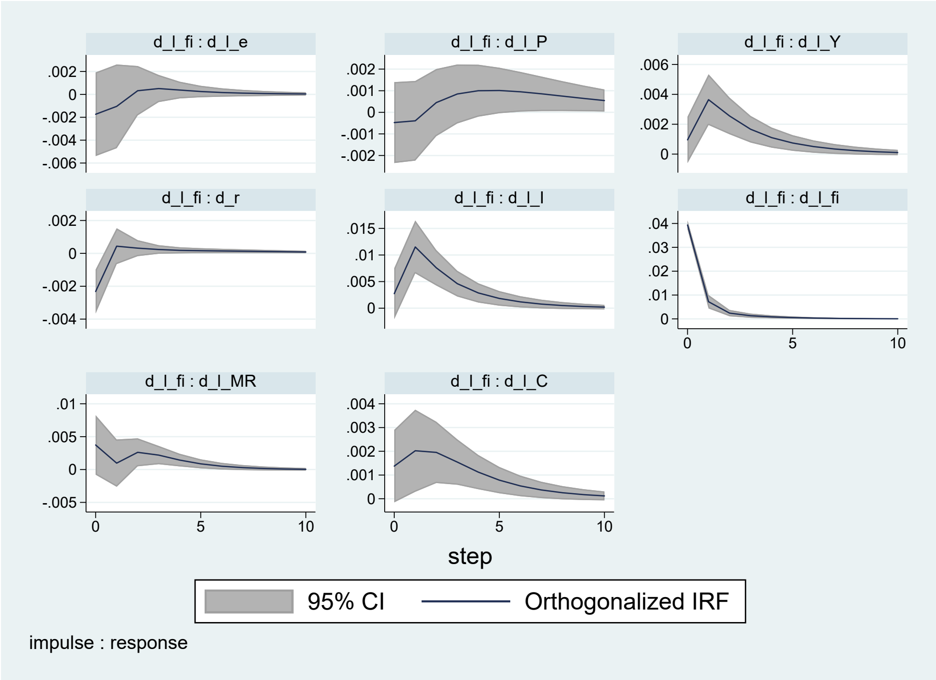


Figure B.82: Cumulative IRF - Impulse on Financial Development, Financial Institution Development (fi), "high" levels

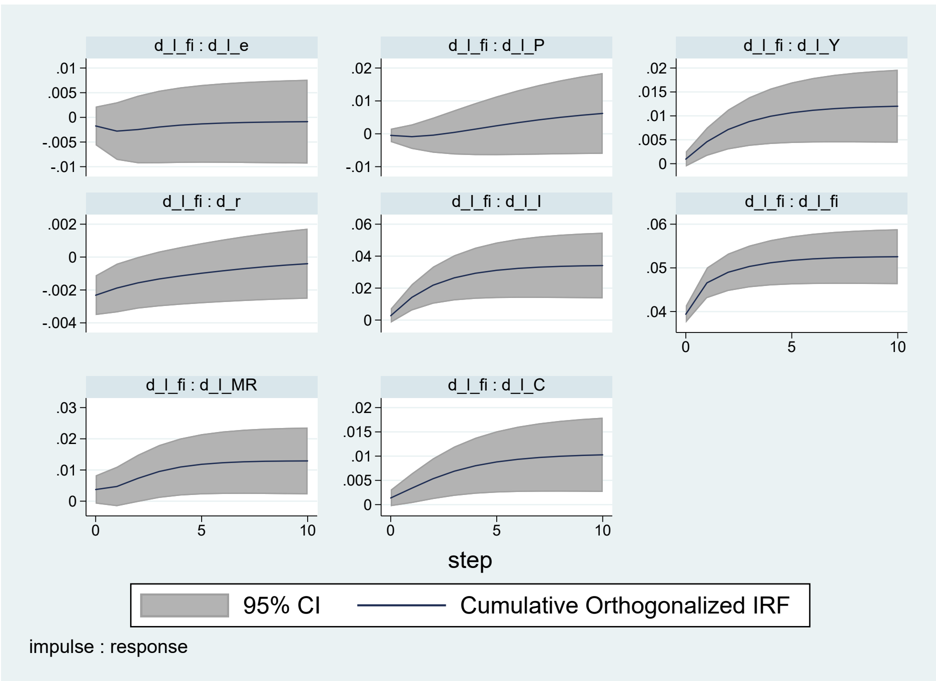


Figure B.83: IRF - Response of Financial Development, Financial Institution Development (fi), “high” levels

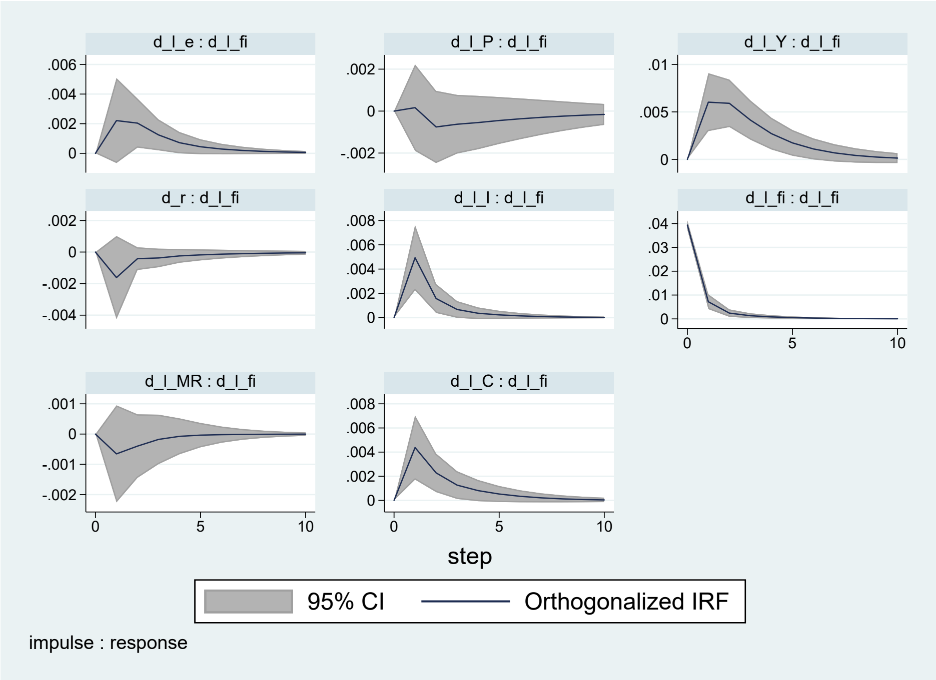


Figure B.84: Cumulative IRF - Response of Financial Development, Financial Institution Development (fi), “high” levels

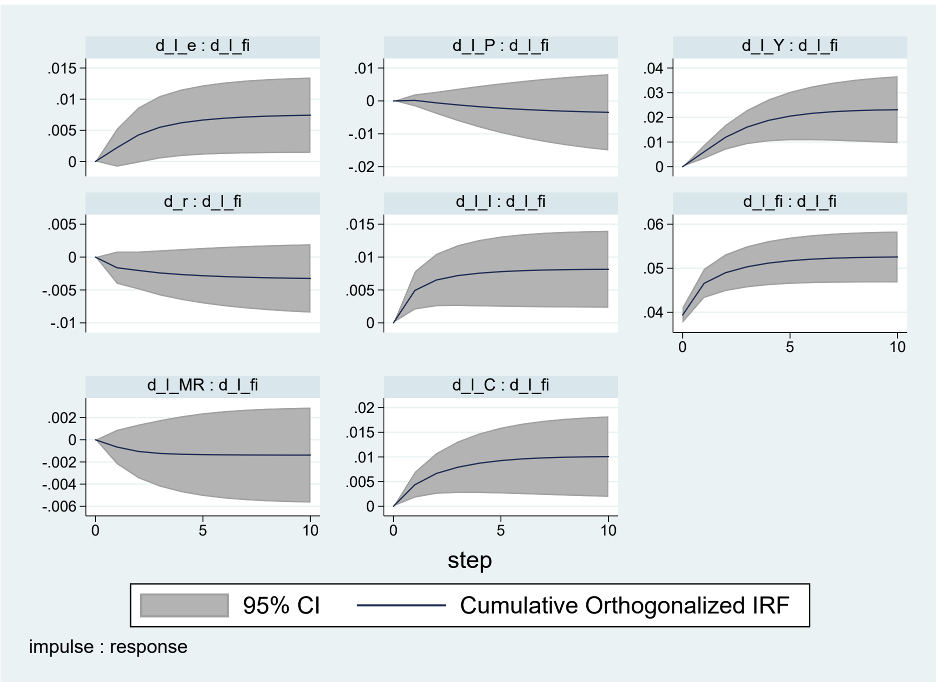


Table B.22: Granger causality tests - Financial Institution Development (fi), "low" levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fi
d_l_e	NA	0.012	0.971	0.001	0.011	0.021	0.977	0.000
d_r	0.006	NA	0.000	0.000	0.863	0.675	0.261	0.001
d_l_MR	0.282	0.001	NA	0.000	0.071	0.378	0.666	0.146
d_l_P	0.000	0.001	0.000	NA	0.098	0.057	0.001	0.000
d_l_I	0.006	0.419	0.829	0.297	NA	0.646	0.543	0.818
d_l_C	0.922	0.632	0.894	0.504	0.075	NA	0.046	0.544
d_l_Y	0.012	0.059	0.368	0.257	0.026	0.009	NA	0.524
d_l_fi	0.261	0.549	0.042	0.195	0.091	0.433	0.742	NA
ALL	0.000	0.000	0.000	0.000	0.020	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.85: IRF - Impulse on Financial Development, Financial Institution Development (fi), “low” levels

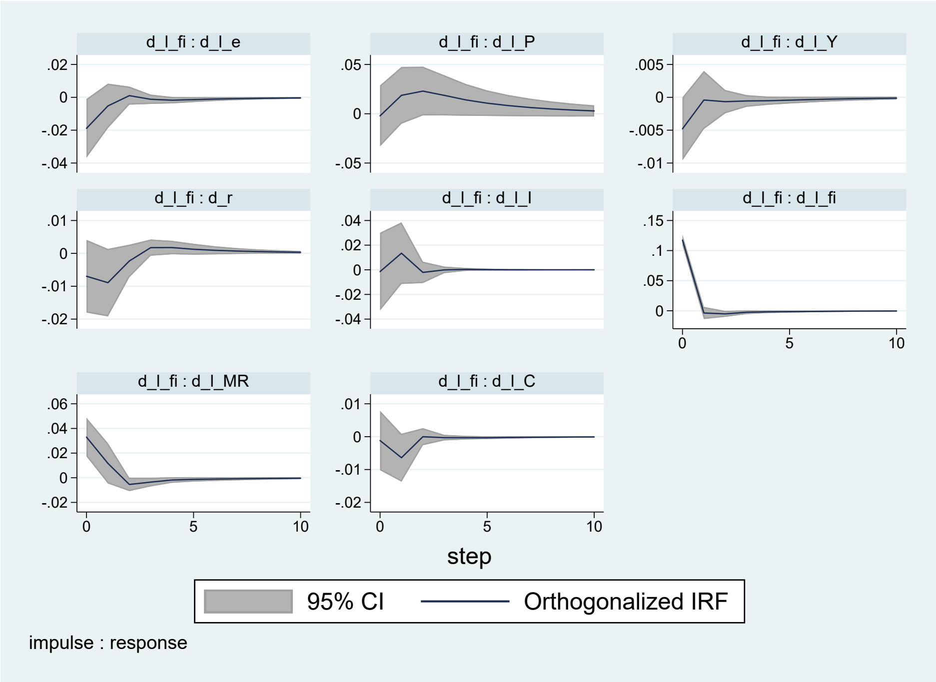


Figure B.86: Cumulative IRF - Impulse on Financial Development, Financial Institution Development (fi), “low” levels

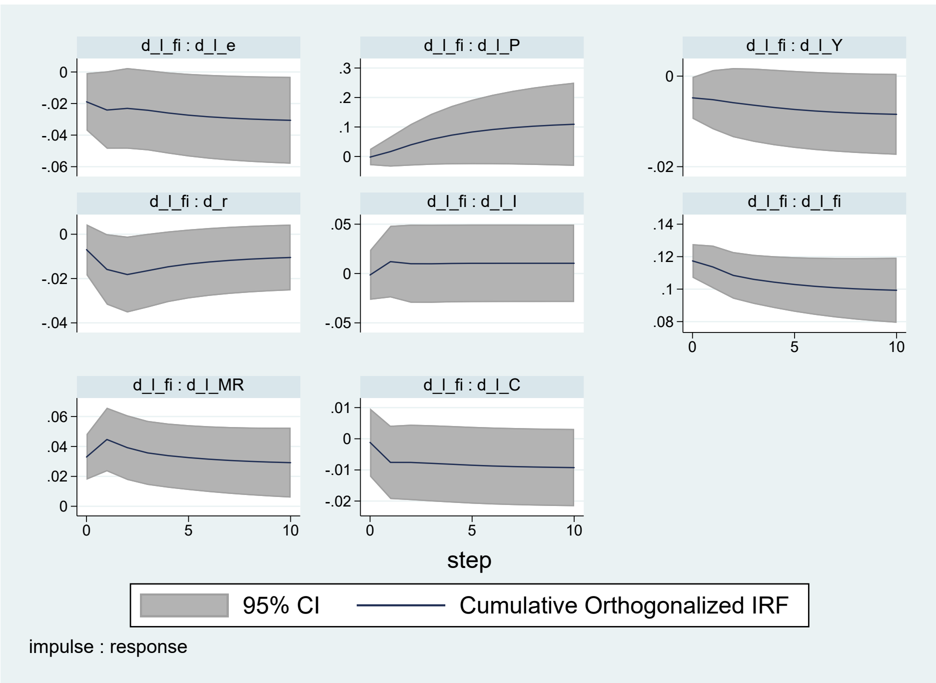


Figure B.87: IRF - Response of Financial Development, Financial Institution Development (fi), "low" levels

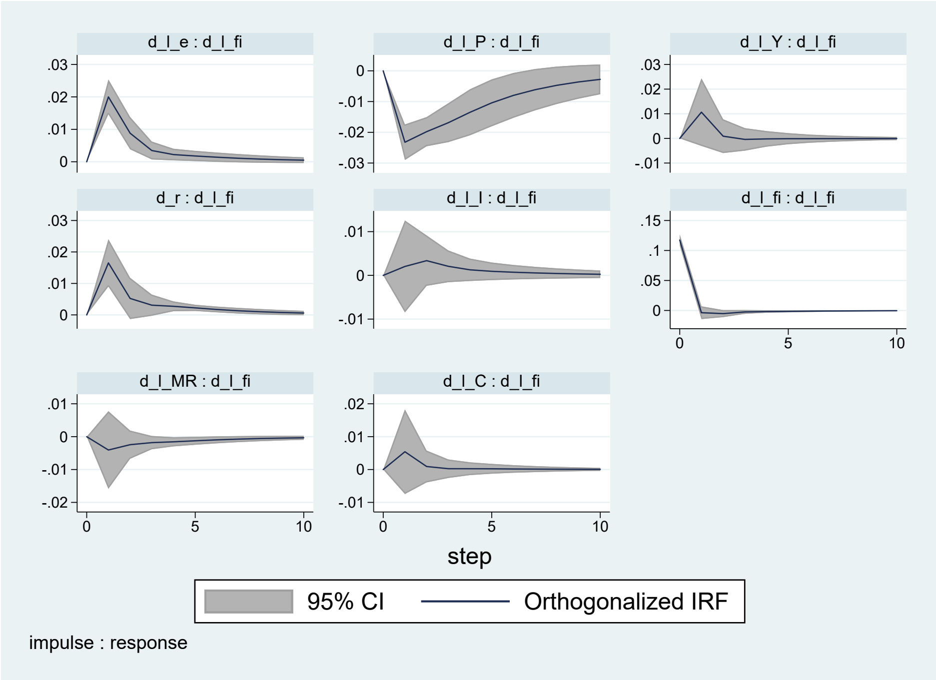
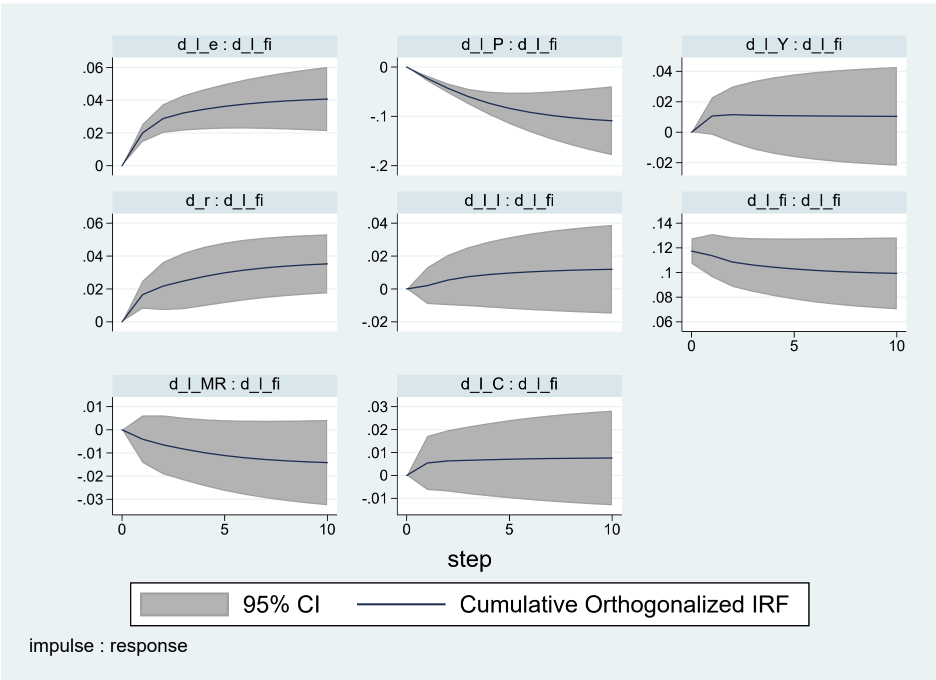


Figure B.88: Cumulative IRF - Response of Financial Development, Financial Institution Development (fi), "low" levels



B.6 Financial Markets Development

Table B.23: Granger causality tests - Financial Markets Development (fm)

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fm
d_l_e	NA	0.006	0.875	0.002	0.056	0.010	0.027	0.000
d_r	0.465	NA	0.001	0.000	0.108	0.117	0.285	0.002
d_l_MR	0.168	0.141	NA	0.034	0.071	0.689	0.590	0.914
d_l_P	0.025	0.000	0.000	NA	0.593	0.582	0.010	0.635
d_l_I	0.028	0.264	0.374	0.325	NA	0.144	0.688	0.088
d_l_C	0.671	0.159	0.199	0.281	0.074	NA	0.212	0.238
d_l_Y	0.513	0.746	0.023	0.336	0.000	0.000	NA	0.317
d_l_fm	0.226	0.872	0.283	0.937	0.002	0.091	0.000	NA
ALL	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.89: IRF - Impulse on Financial Development, Financial Markets Development (fm)

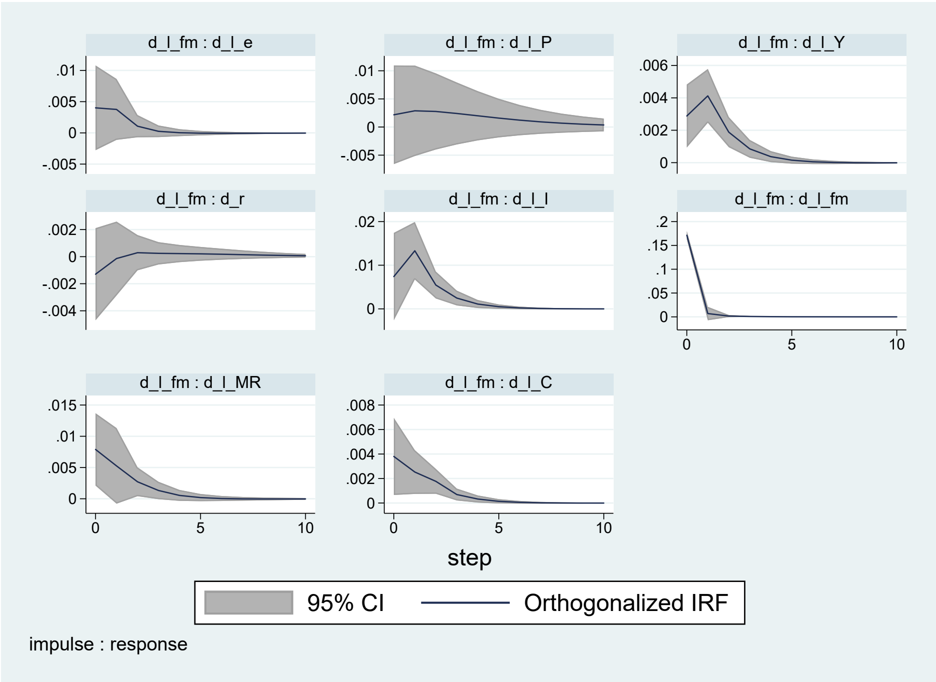


Figure B.90: Cumulative IRF - Impulse on Financial Development, Financial Markets Development (fm)

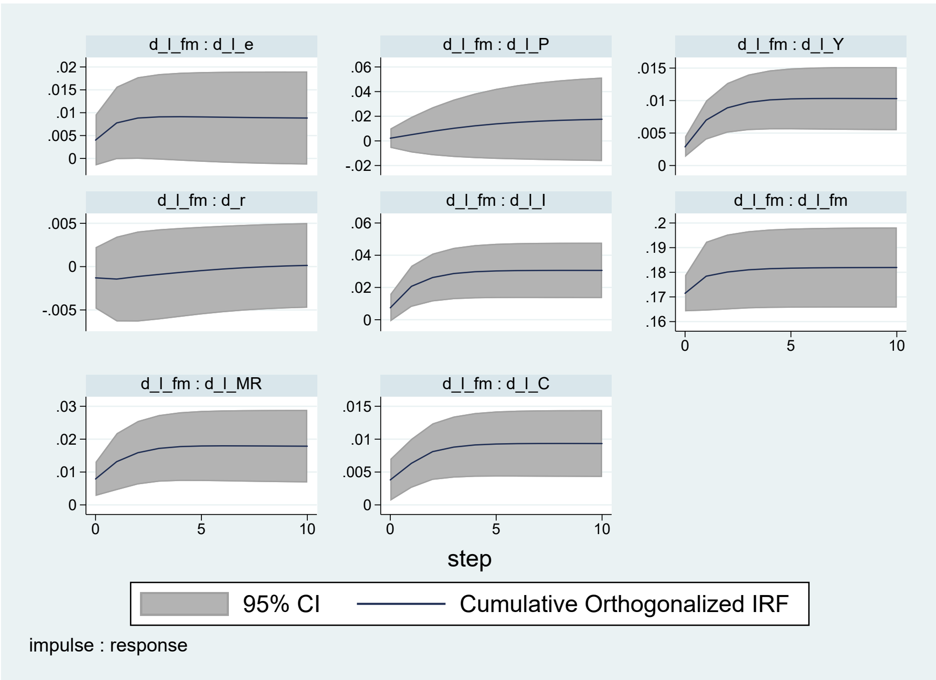


Figure B.91: IRF - Response of Financial Development, Financial Markets Development (fm)

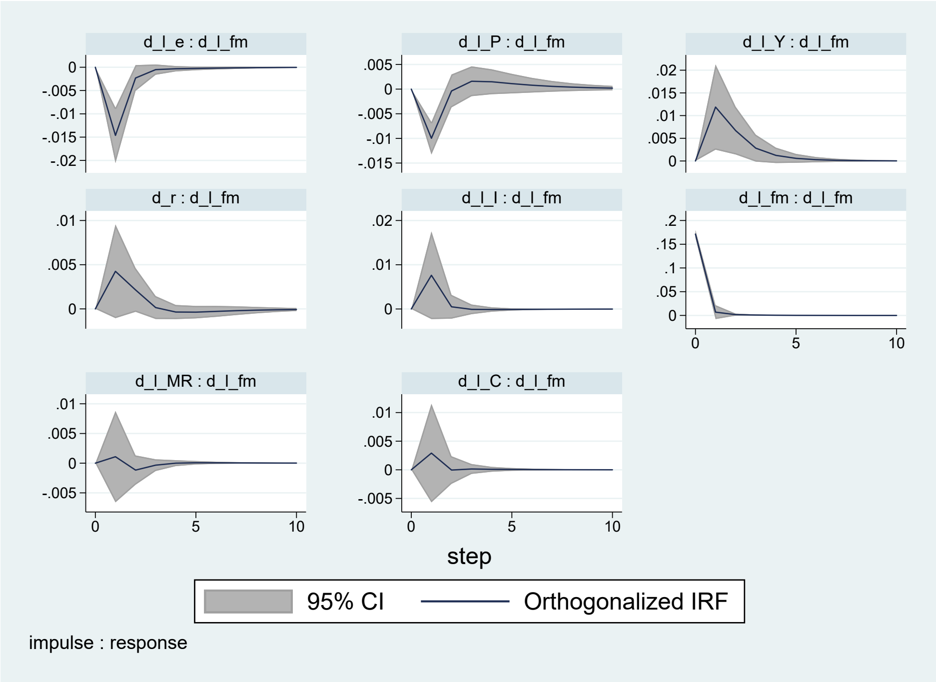


Figure B.92: Cumulative IRF - Response of Financial Development, Financial Markets Development (fm)

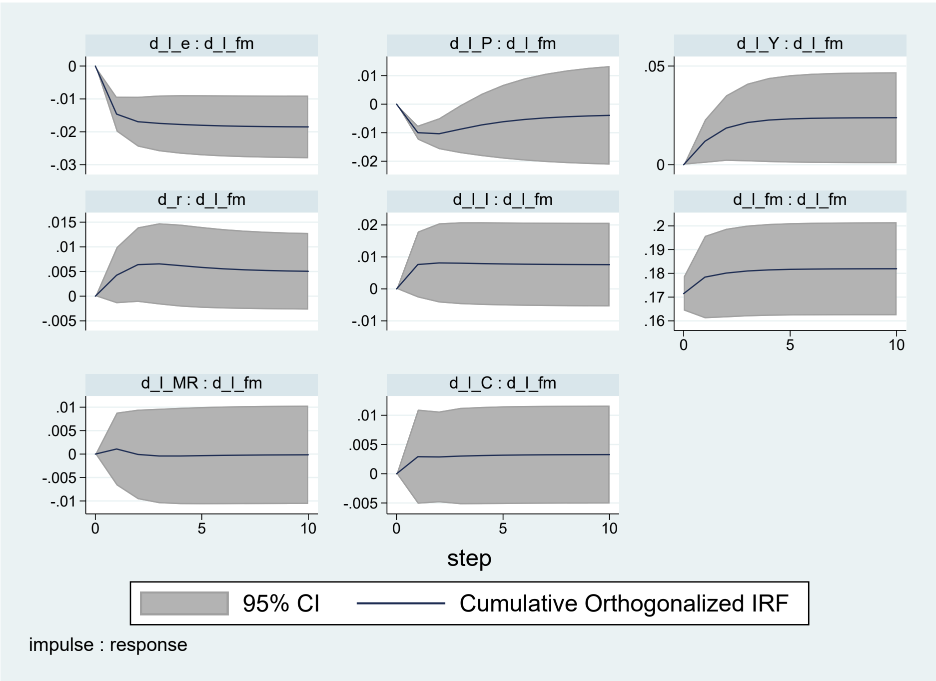


Table B.24: Granger causality tests - Financial Markets Development (fm), “high” levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fm
d_l_e	NA	0.001	0.026	0.000	0.000	0.025	0.978	0.000
d_r	0.000	NA	0.020	0.000	0.511	0.438	0.113	0.000
d_l_MR	0.566	0.587	NA	0.481	0.301	0.079	0.767	0.438
d_l_P	0.266	0.000	0.004	NA	0.472	0.134	0.997	0.003
d_l_I	0.940	0.044	0.789	0.155	NA	0.233	0.119	0.016
d_l_C	0.661	0.027	0.793	0.018	0.521	NA	0.009	0.000
d_l_Y	0.183	0.146	0.003	0.848	0.000	0.000	NA	0.000
d_l_fm	0.556	0.398	0.574	0.886	0.000	0.000	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.93: IRF - Impulse on Financial Development, Financial Markets Development (fm), “high” levels

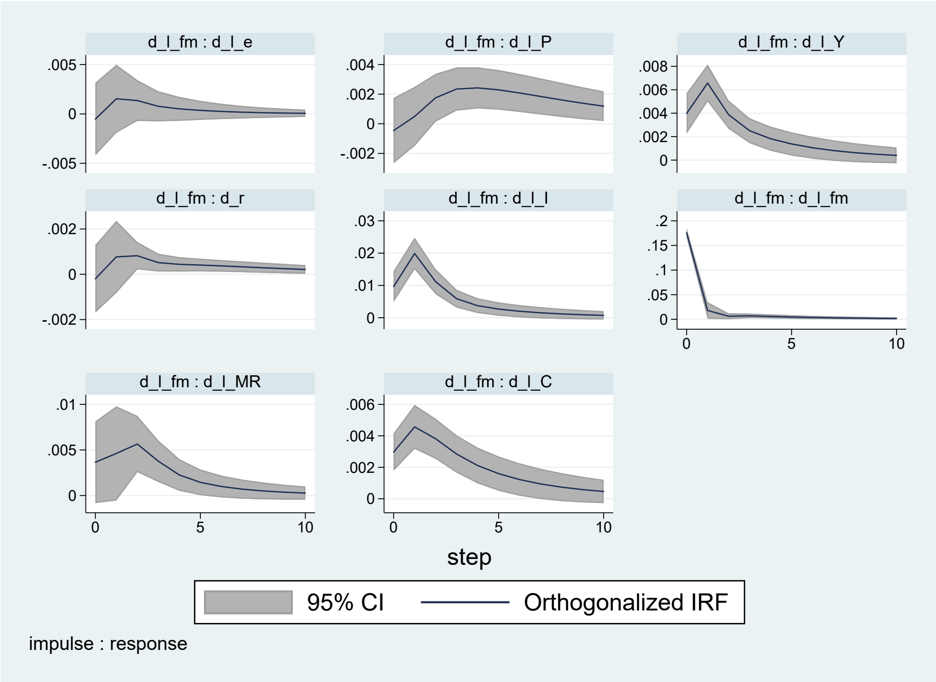


Figure B.94: Cumulative IRF - Impulse on Financial Development, Financial Markets Development (fm), “high” levels

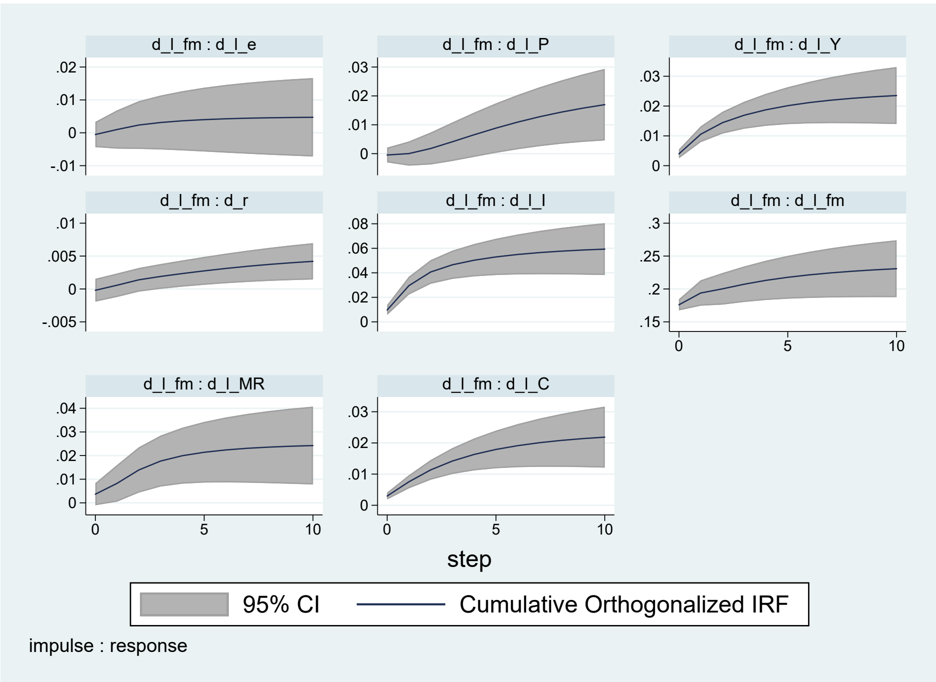


Figure B.95: IRF - Response of Financial Development, Financial Markets Development (fm), “high” levels

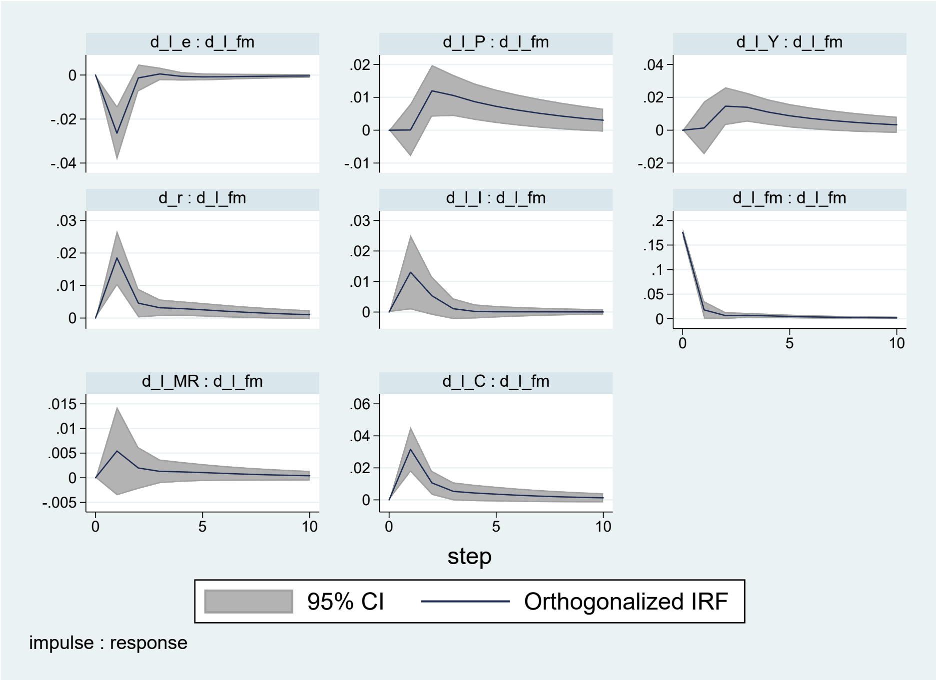


Figure B.96: Cumulative IRF - Response of Financial Development, Financial Markets Development (fm), “high” levels

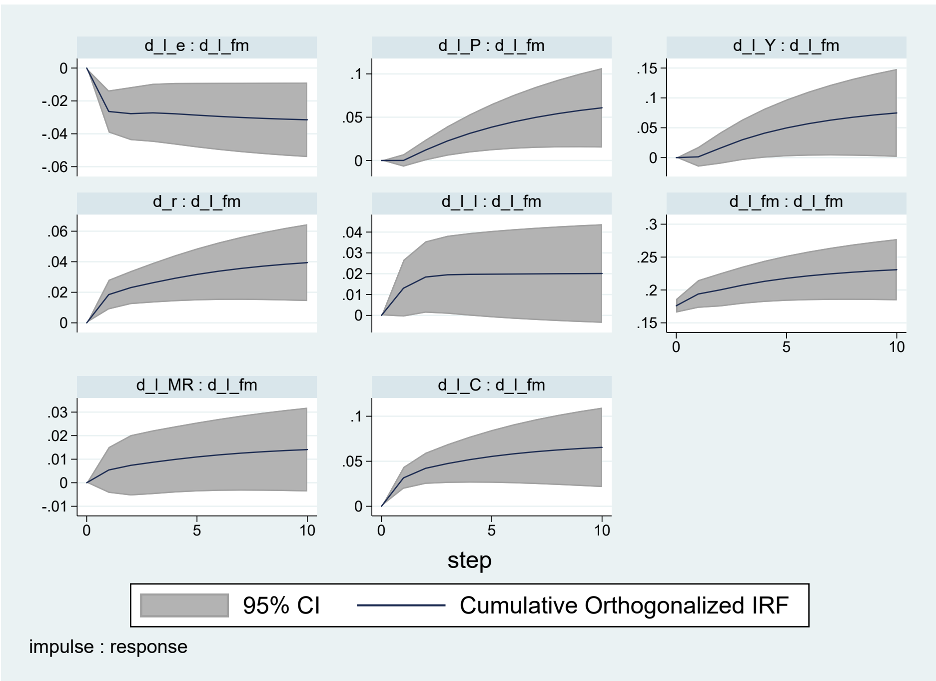


Table B.25: Granger causality tests - Financial Markets Development (fm), "low" levels

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fm
d_l_e	NA	0.039	0.179	0.002	0.000	0.026	0.284	0.608
d_r	0.391	NA	0.000	0.000	0.005	0.145	0.118	0.053
d_l_MR	0.780	0.002	NA	0.000	0.033	0.144	0.512	0.745
d_l_P	0.004	0.000	0.000	NA	0.971	0.206	0.010	0.000
d_l_I	0.019	0.485	0.660	0.323	NA	0.144	0.850	0.142
d_l_C	0.917	0.590	0.973	0.968	0.075	NA	0.091	0.916
d_l_Y	0.336	0.281	0.570	0.727	0.067	0.000	NA	0.591
d_l_fm	0.556	0.688	0.092	0.941	0.892	0.789	0.329	NA
ALL	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.97: IRF - Impulse on Financial Development, Financial Markets Development (fm), “low” levels

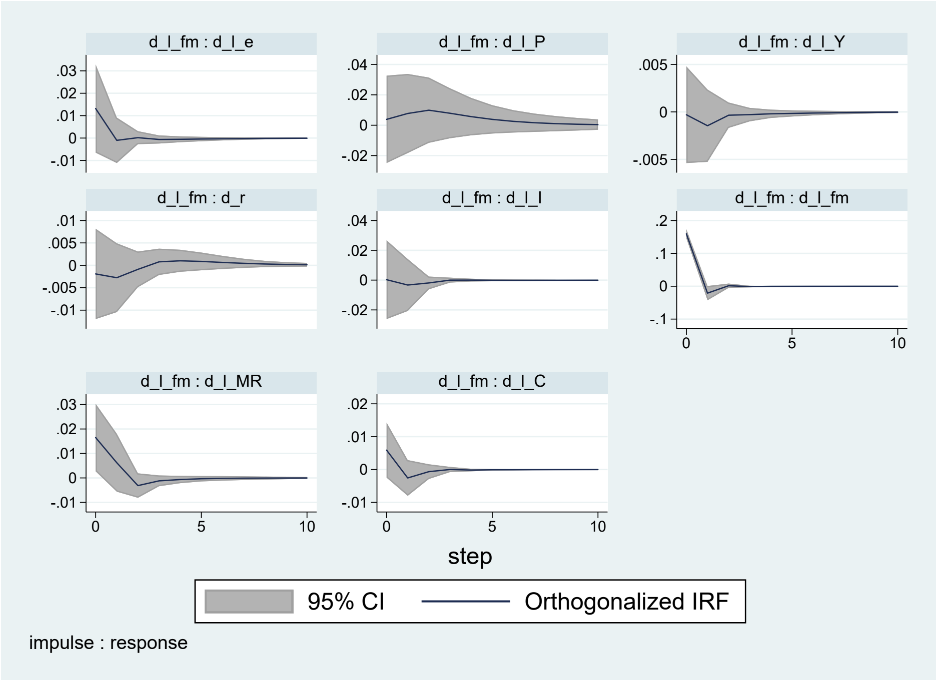


Figure B.98: Cumulative IRF - Impulse on Financial Development, Financial Markets Development (fm), “low” levels

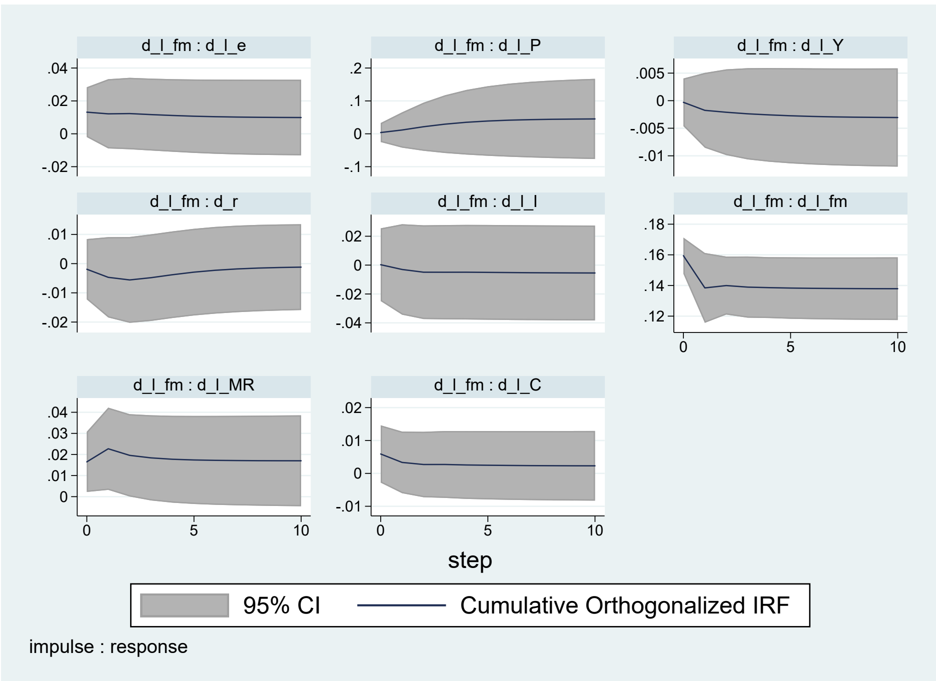


Figure B.99: IRF - Response of Financial Development, Financial Markets Development (fm), “low” levels

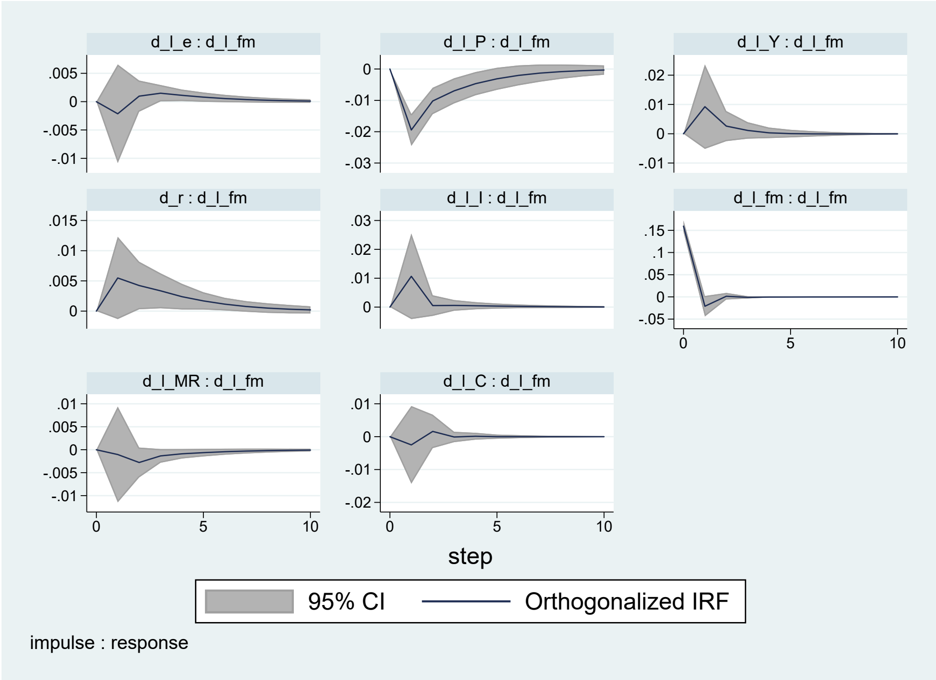
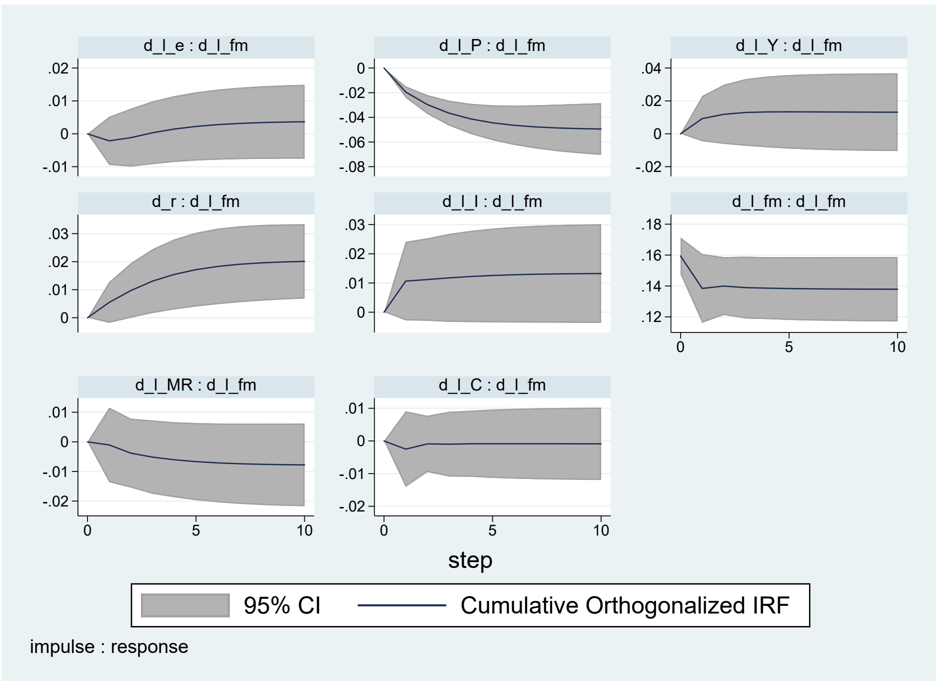


Figure B.100: Cumulative IRF - Response of Financial Development, Financial Markets Development (fm), “low” levels



B.7 Financial Structure

Table B.26: Granger causality tests - Market based

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.004	0.161	0.001	0.001	0.116	0.548	0.000
d_r	0.000	NA	0.353	0.000	0.000	0.153	0.611	0.000
d_l_MR	0.595	0.000	NA	0.000	0.004	0.042	0.663	0.641
d_l_P	0.045	0.000	0.000	NA	0.000	0.066	0.443	0.044
d_l_I	0.000	0.154	0.000	0.000	NA	0.000	0.000	0.000
d_l_C	0.000	0.016	0.014	0.317	0.163	NA	0.958	0.005
d_l_Y	0.000	0.061	0.127	0.001	0.000	0.000	NA	0.089
d_l_fd	0.041	0.388	0.171	0.881	0.000	0.091	0.000	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.101: IRF - Impulse on Financial Development, Market based

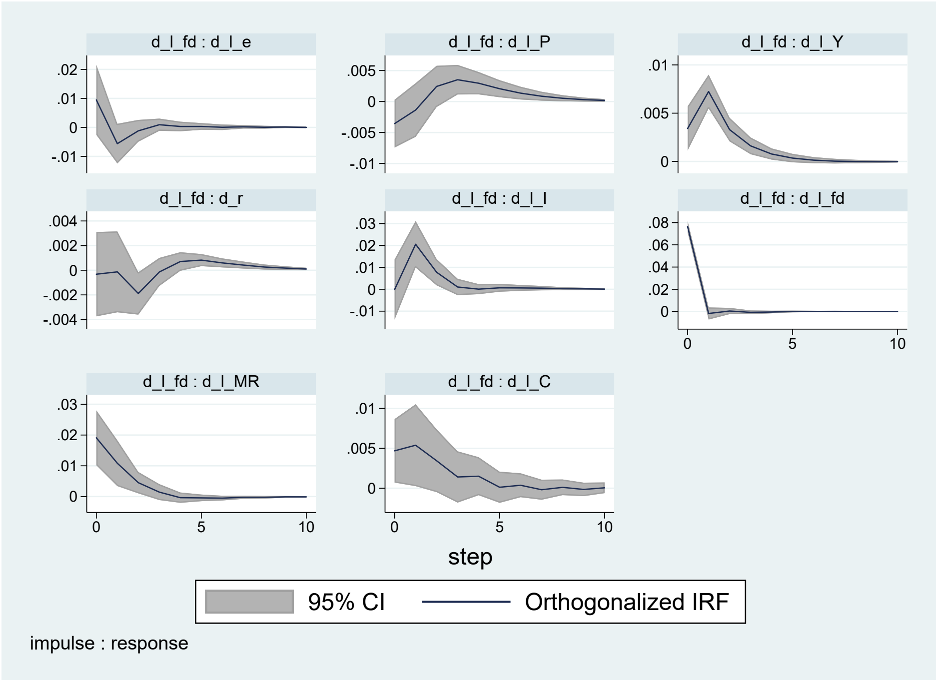


Figure B.102: Cumulative IRF - Impulse on Financial Development, Market based

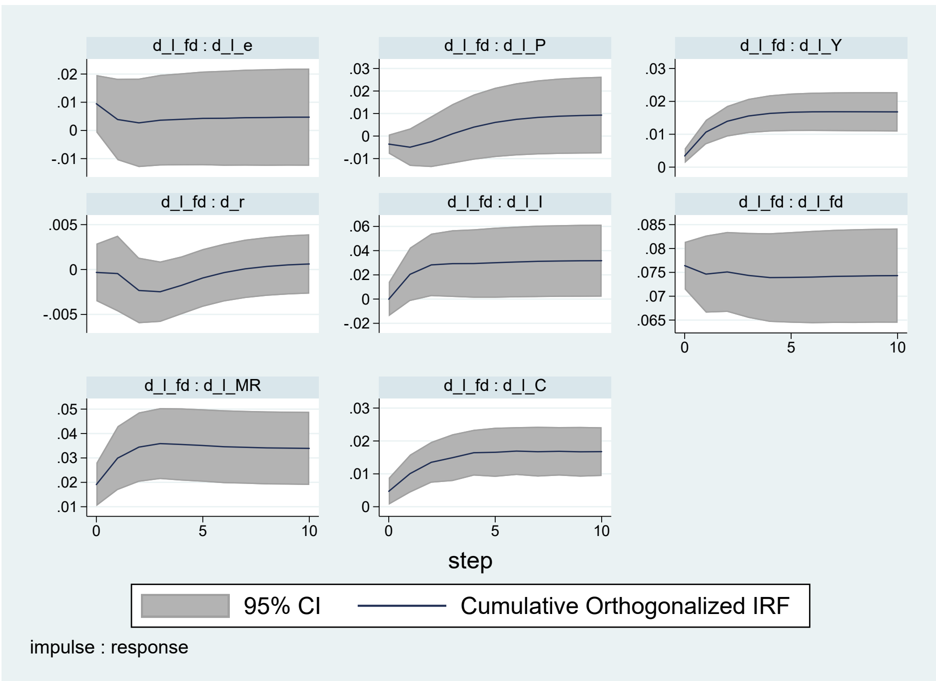


Figure B.103: IRF - Response of Financial Development, Market based

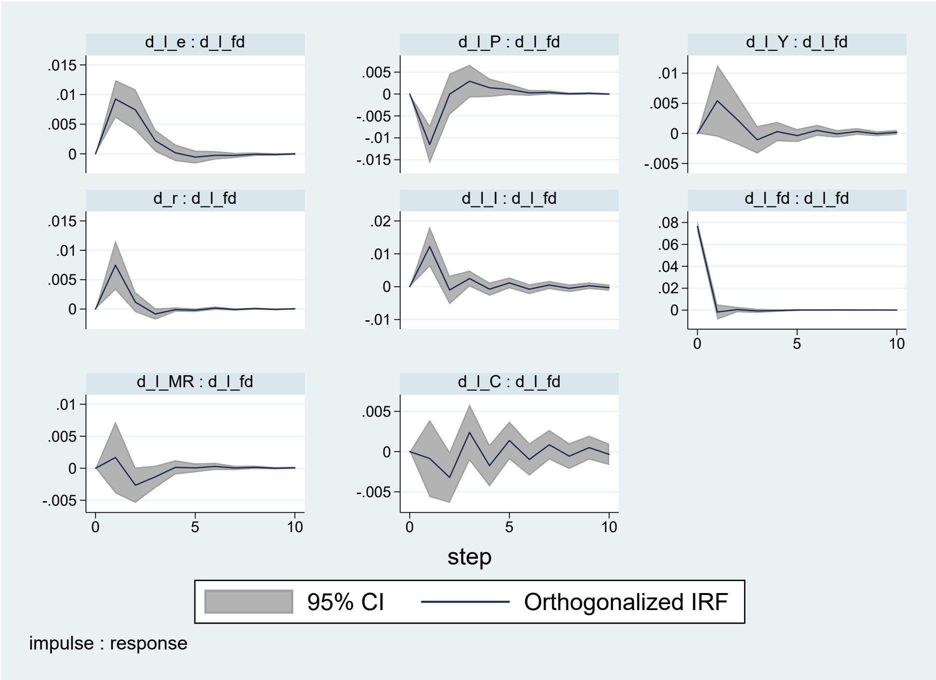


Figure B.104: Cumulative IRF - Response of Financial Development, Market based

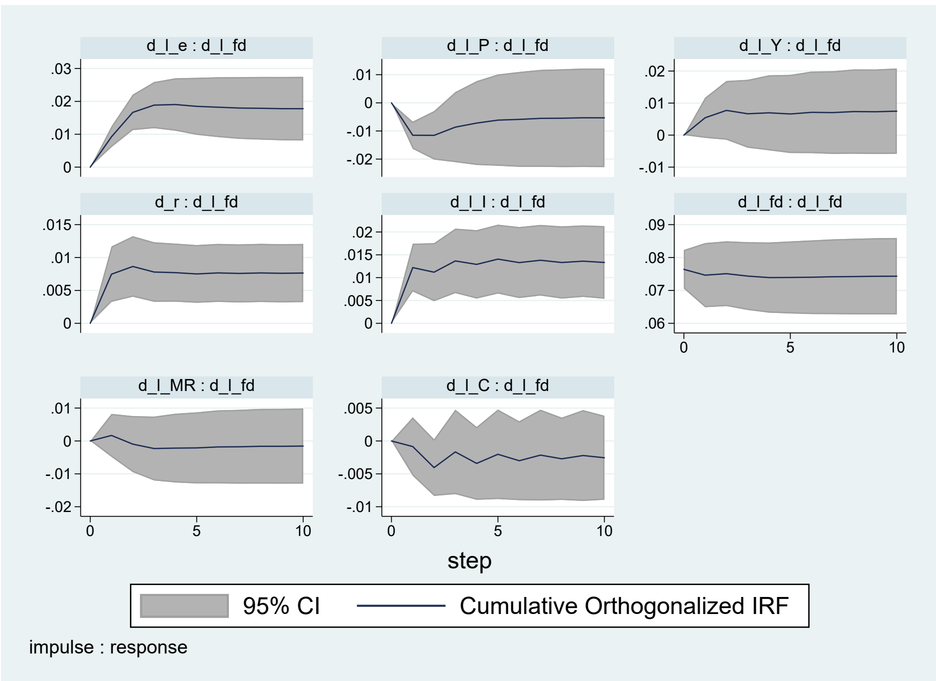


Table B.27: Granger causality tests - Bank based

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.913	0.140	0.364	0.312	0.011	0.025	0.000
d_r	0.462	NA	0.005	0.000	0.764	0.199	0.617	0.000
d_l_MR	0.016	0.333	NA	0.140	0.514	0.508	0.665	0.417
d_l_P	0.001	0.000	0.000	NA	0.014	0.261	0.515	0.000
d_l_I	0.069	0.012	0.226	0.177	NA	0.293	0.550	0.538
d_l_C	0.068	0.137	0.224	0.007	0.668	NA	0.550	0.837
d_l_Y	0.764	0.851	0.036	0.041	0.000	0.000	NA	0.042
d_l_fd	0.183	0.245	0.418	0.012	0.001	0.079	0.003	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.105: IRF - Impulse on Financial Development, Bank based

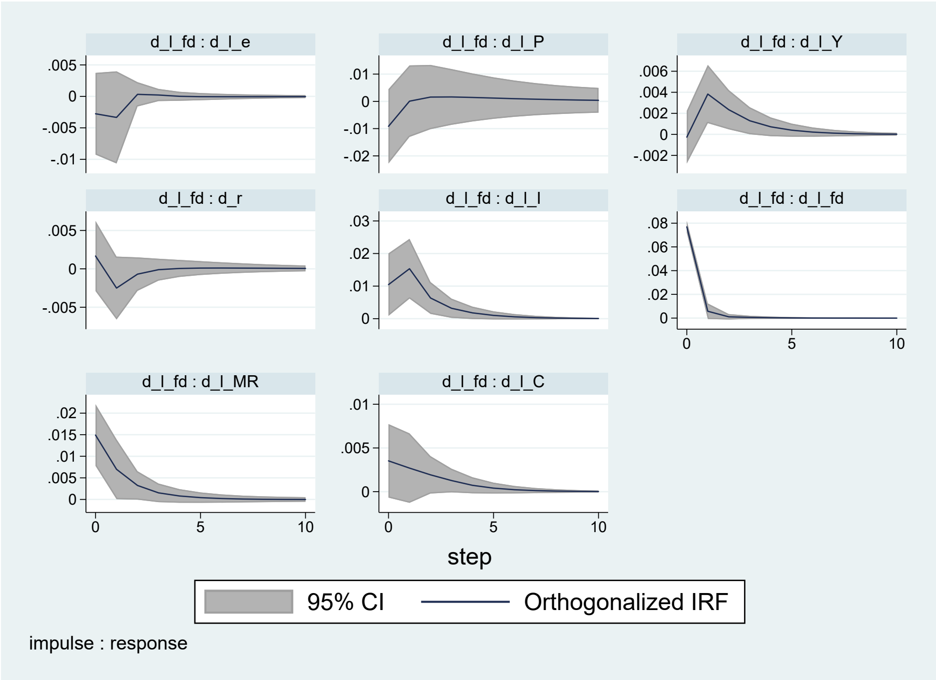


Figure B.106: Cumulative IRF - Impulse on Financial Development, Bank based

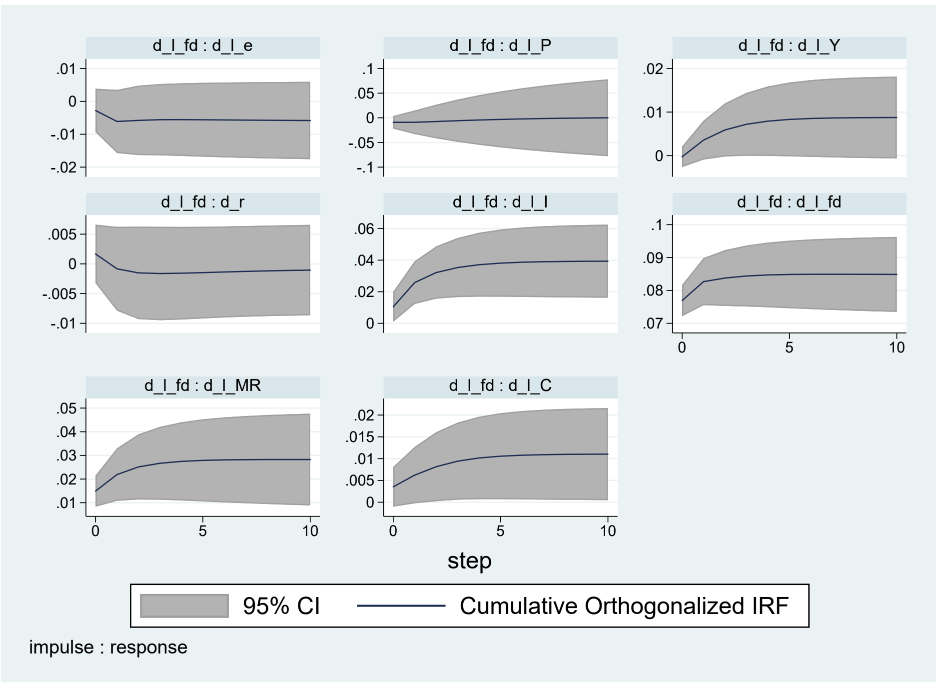


Figure B.107: IRF - Response of Financial Development, Bank based

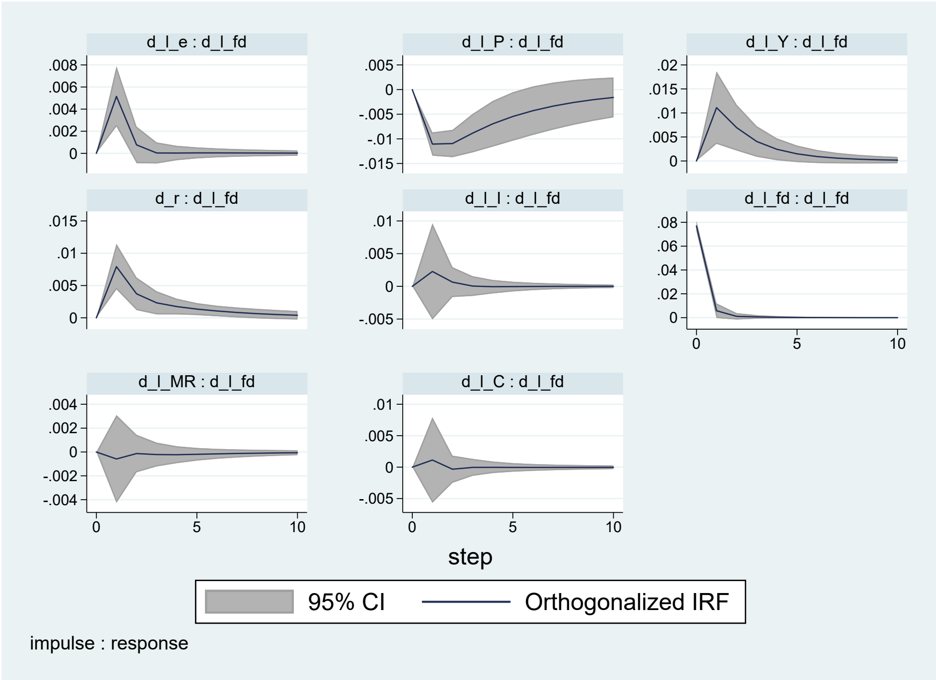
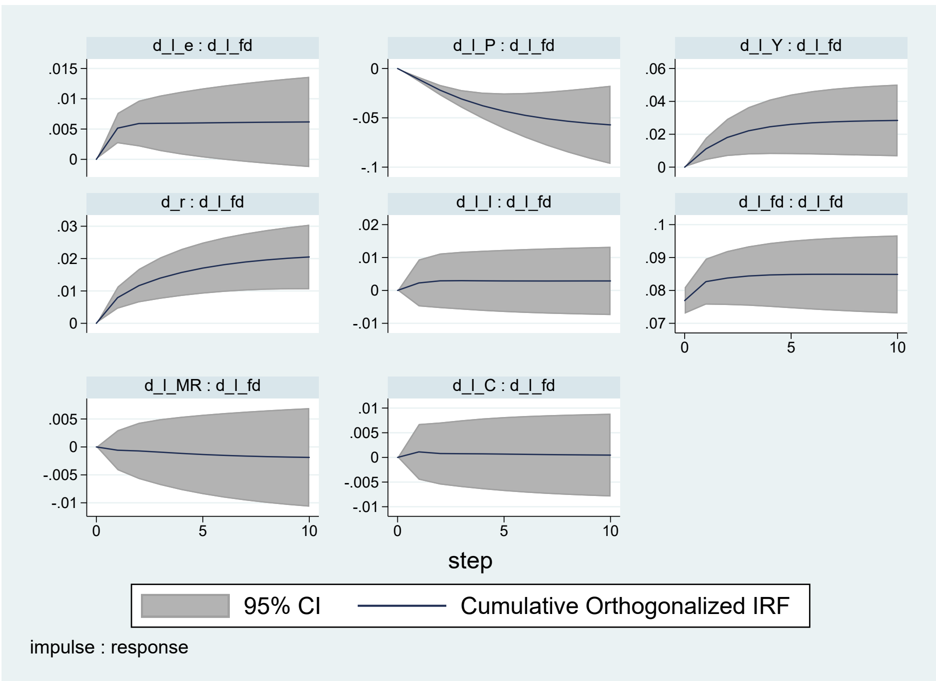


Figure B.108: Cumulative IRF - Response of Financial Development, Bank based



B.8 Economic Development

Table B.28: Granger causality tests - “High” Economic Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.001	0.441	0.000	0.020	0.013	0.551	0.237
d_r	0.049	NA	0.087	0.000	0.961	0.295	0.471	0.406
d_l_MR	0.529	0.862	NA	0.793	0.267	0.916	0.983	0.727
d_l_P	0.920	0.003	0.097	NA	0.078	0.450	0.447	0.930
d_l_I	0.722	0.000	0.000	0.805	NA	0.437	0.027	0.018
d_l_C	0.040	0.001	0.963	0.000	0.564	NA	0.031	0.011
d_l_Y	0.015	0.523	0.186	0.781	0.001	0.018	NA	0.871
d_l_fd	0.272	0.948	0.691	0.080	0.000	0.000	0.000	NA
ALL	0.050	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.109: IRF - Impulse on Financial Development, “High” Economic Development

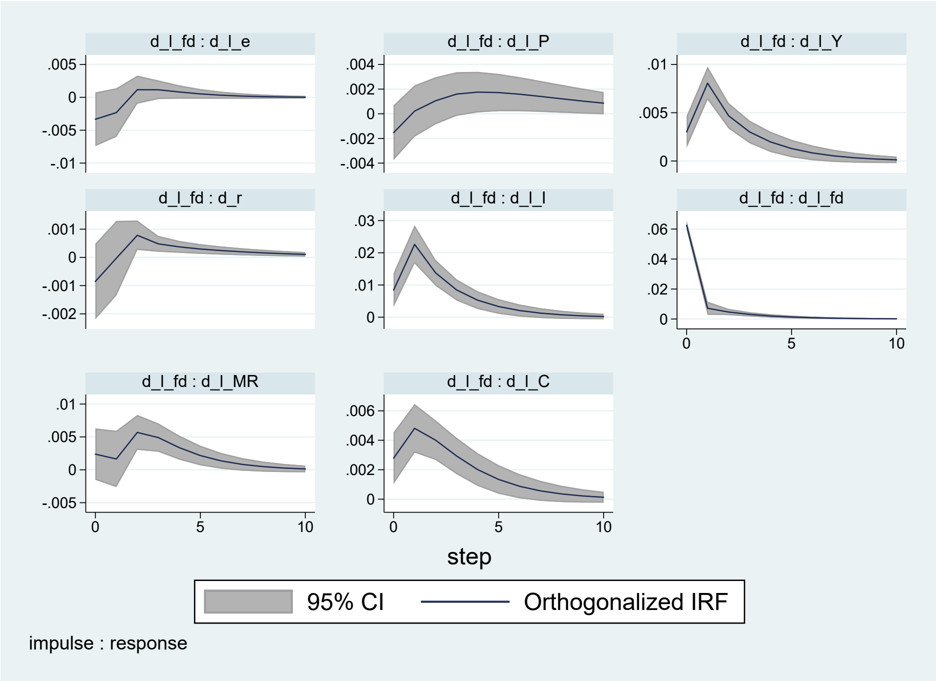


Figure B.110: Cumulative IRF - Impulse on Financial Development, “High” Economic Development

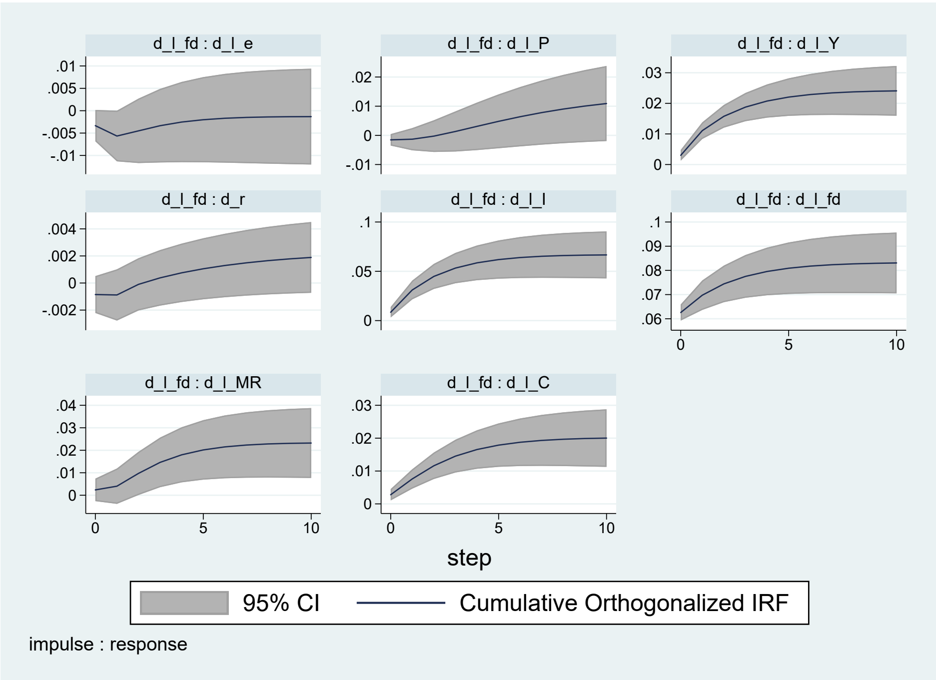


Figure B.111: IRF - Response of Financial Development, “High” Economic Development

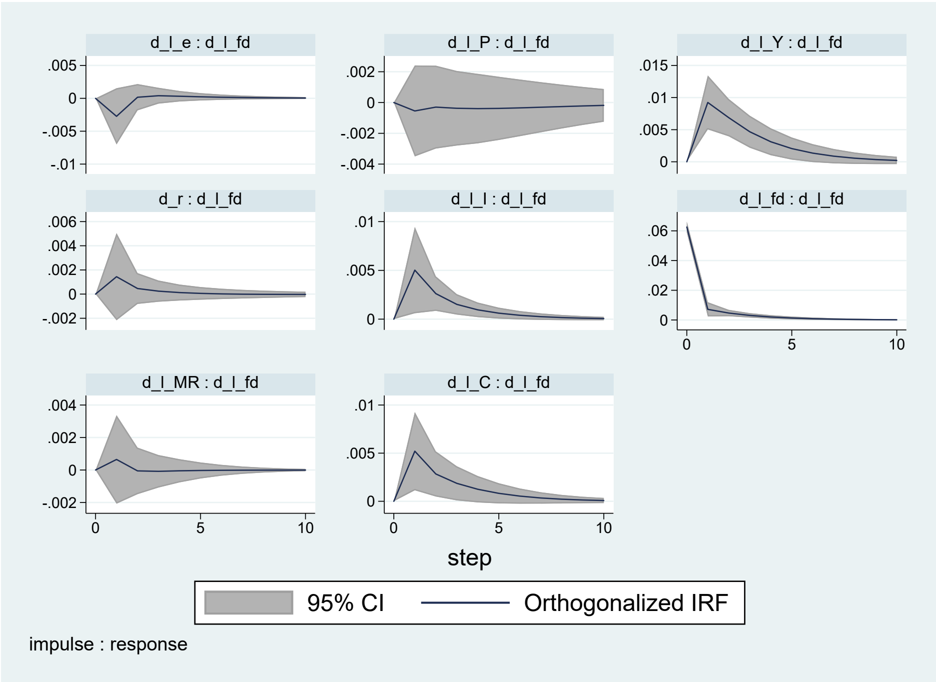


Figure B.112: Cumulative IRF - Response of Financial Development, “High” Economic Development

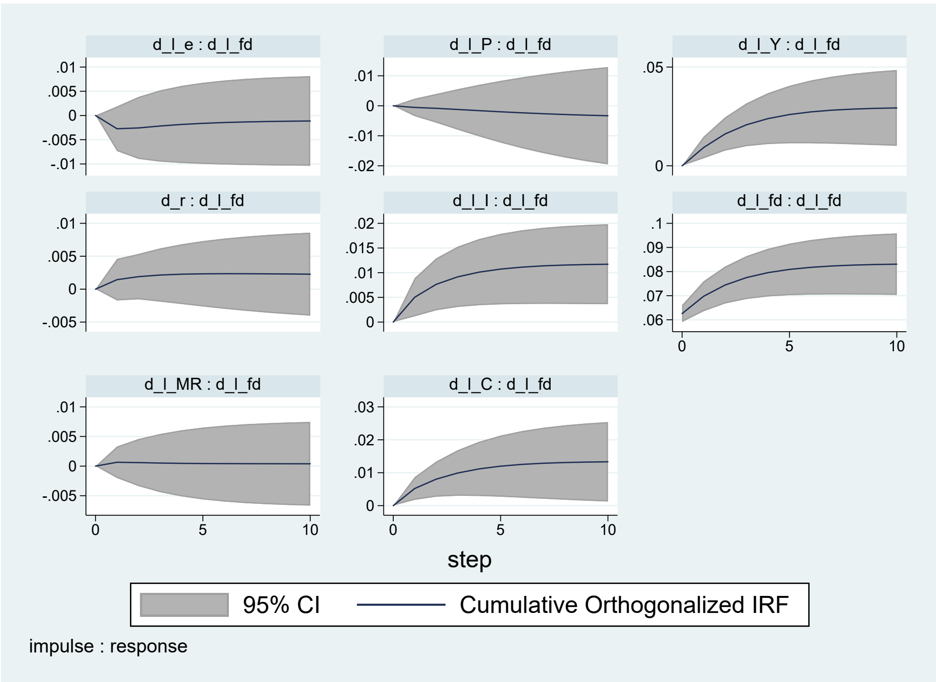


Table B.29: Granger causality tests - “Low” Economic Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.019	0.535	0.012	0.012	0.038	0.373	0.000
d_r	0.092	NA	0.002	0.000	0.897	0.834	0.195	0.011
d_l_MR	0.631	0.006	NA	0.000	0.056	0.430	0.370	0.021
d_l_P	0.001	0.000	0.000	NA	0.257	0.041	0.007	0.000
d_l_I	0.086	0.461	0.703	0.298	NA	0.550	0.891	0.052
d_l_C	0.941	0.873	0.878	0.739	0.295	NA	0.008	0.953
d_l_Y	0.451	0.297	0.038	0.795	0.001	0.028	NA	0.754
d_l_fd	0.066	0.397	0.013	0.154	0.238	0.278	0.202	NA
ALL	0.005	0.000	0.000	0.000	0.002	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.113: IRF - Impulse on Financial Development, “Low” Economic Development

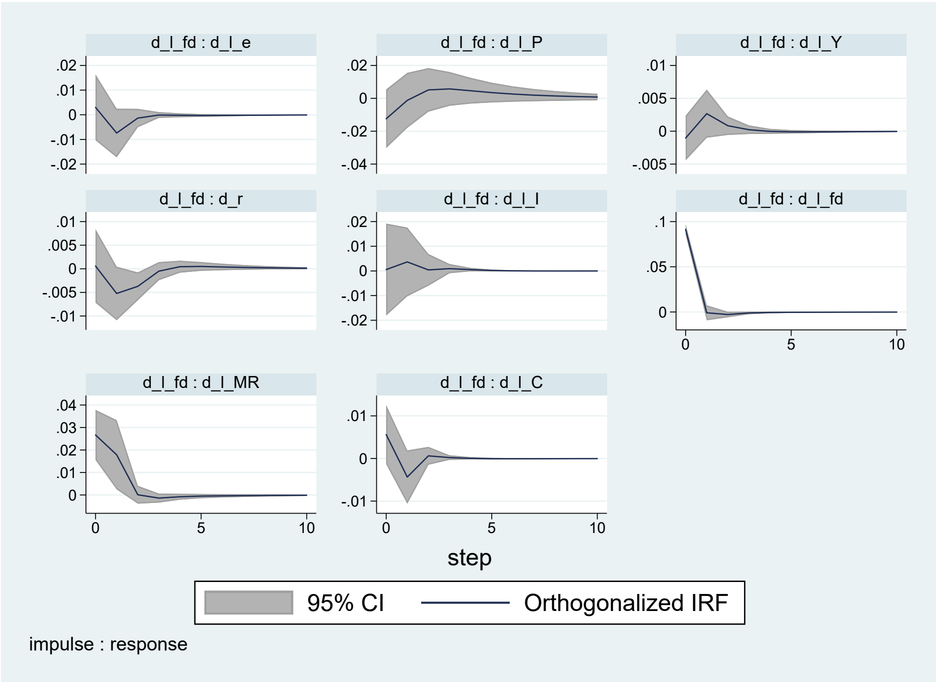


Figure B.114: Cumulative IRF - Impulse on Financial Development, “Low” Economic Development

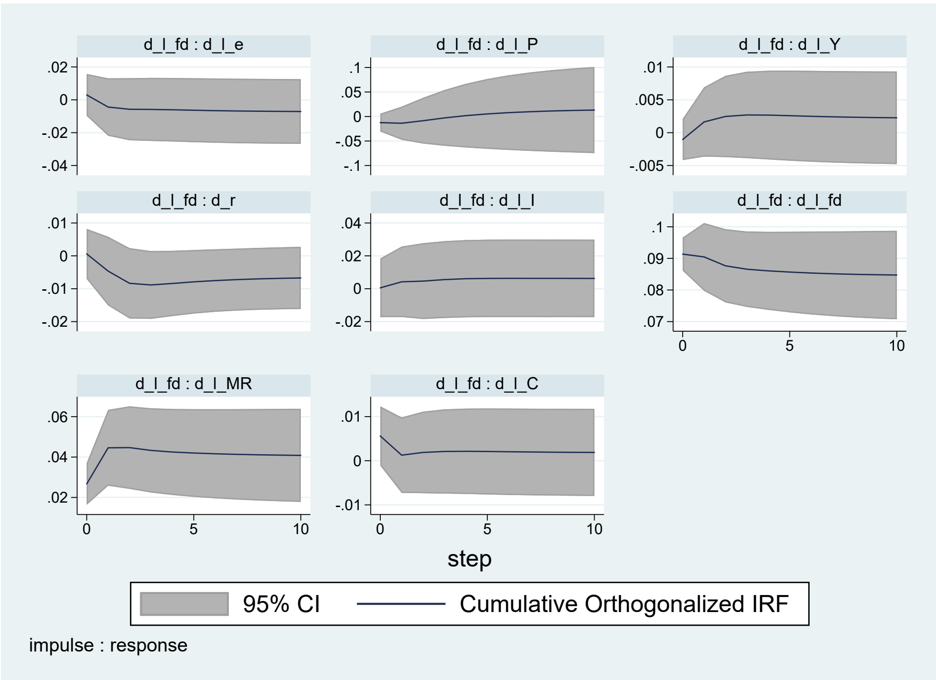


Figure B.115: IRF - Response of Financial Development, "Low" Economic Development

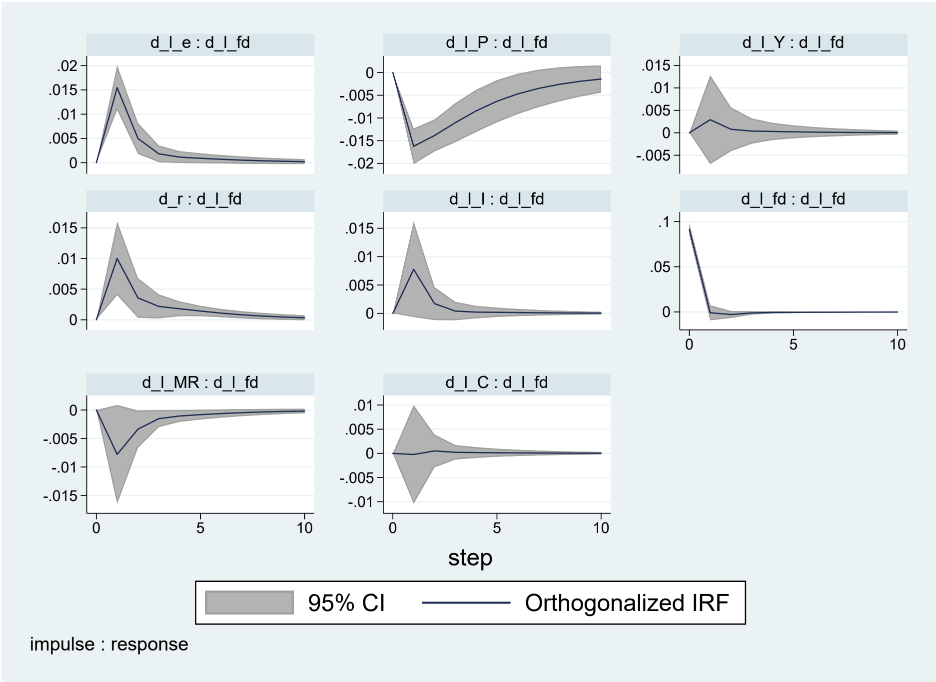
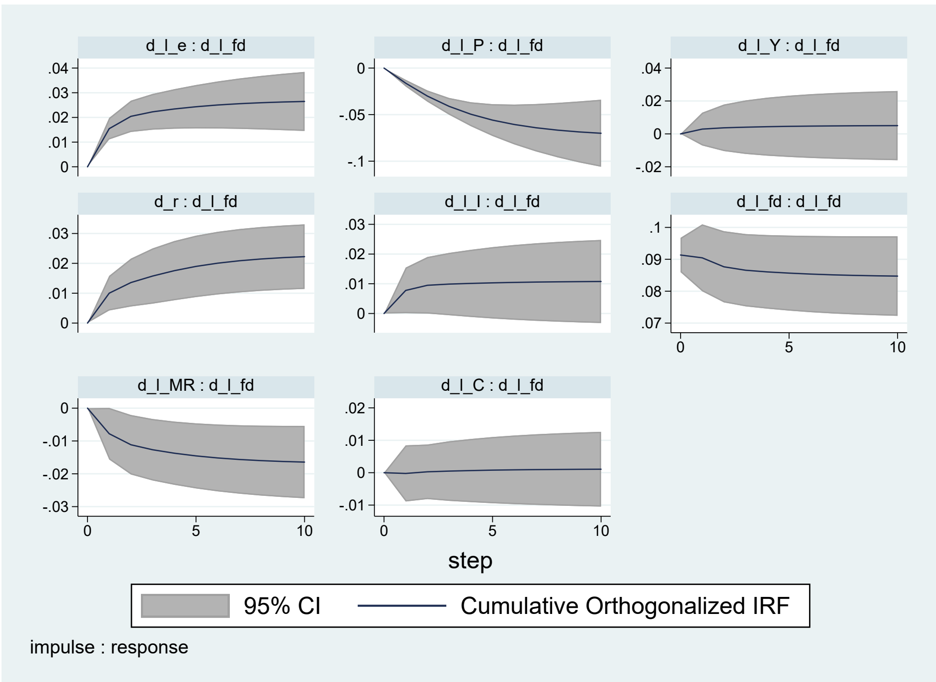


Figure B.116: Cumulative IRF - Response of Financial Development, "Low" Economic Development



B.9 Doing Business Index

Table B.30: Granger causality tests - "High" Doing Business Index

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.030	0.177	0.000	0.003	0.051	0.666	0.289
d_r	0.293	NA	0.042	0.000	0.861	0.786	0.598	0.333
d_l_MR	0.839	0.897	NA	0.508	0.123	0.363	0.999	0.593
d_l_P	0.651	0.000	0.606	NA	0.120	0.973	0.623	0.228
d_l_I	0.703	0.011	0.101	0.942	NA	0.832	0.730	0.004
d_l_C	0.188	0.854	0.383	0.432	0.005	NA	0.279	0.011
d_l_Y	0.012	0.798	0.054	0.045	0.000	0.001	NA	0.434
d_l_fd	0.874	0.789	0.596	0.242	0.000	0.000	0.000	NA
ALL	0.187	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.117: IRF - Impulse on Financial Development, “High” Doing Business Index

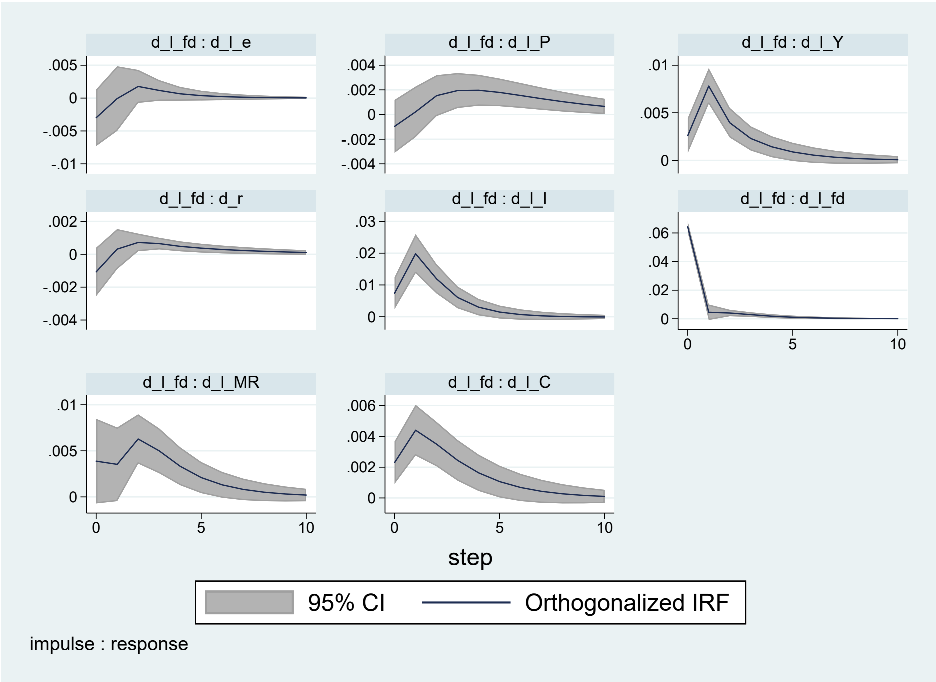


Figure B.118: Cumulative IRF - Impulse on Financial Development, “High” Doing Business Index

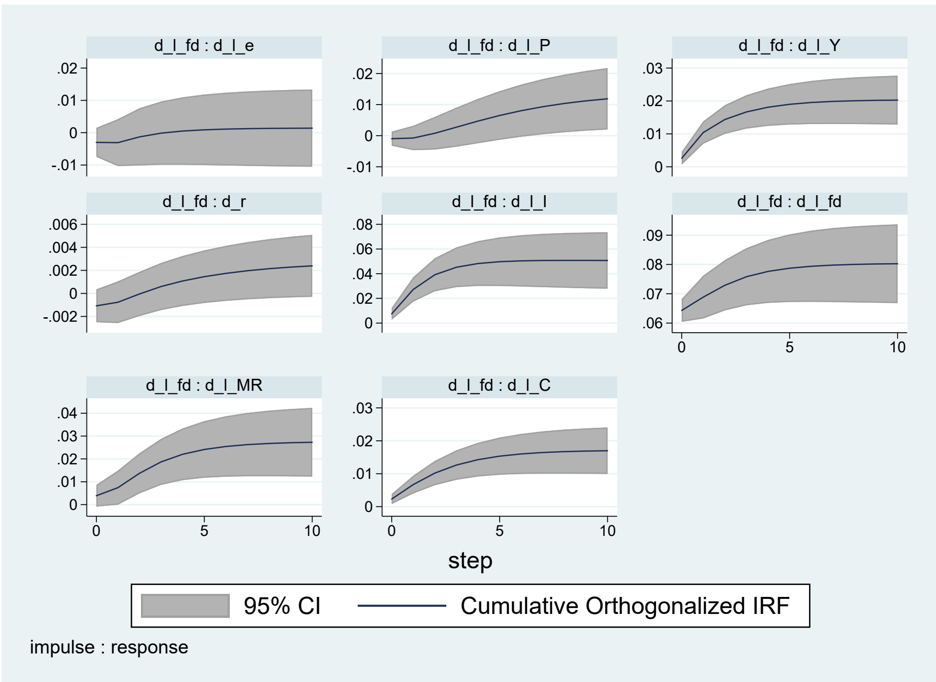


Figure B.119: IRF - Response of Financial Development, “High” Doing Business Index

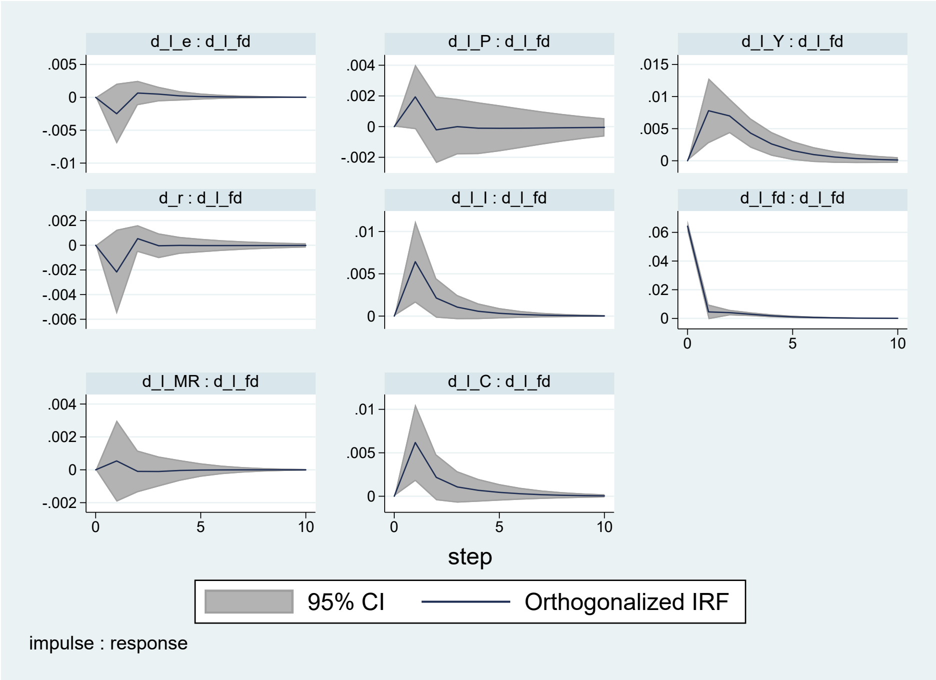


Figure B.120: Cumulative IRF - Response of Financial Development, “High” Doing Business Index

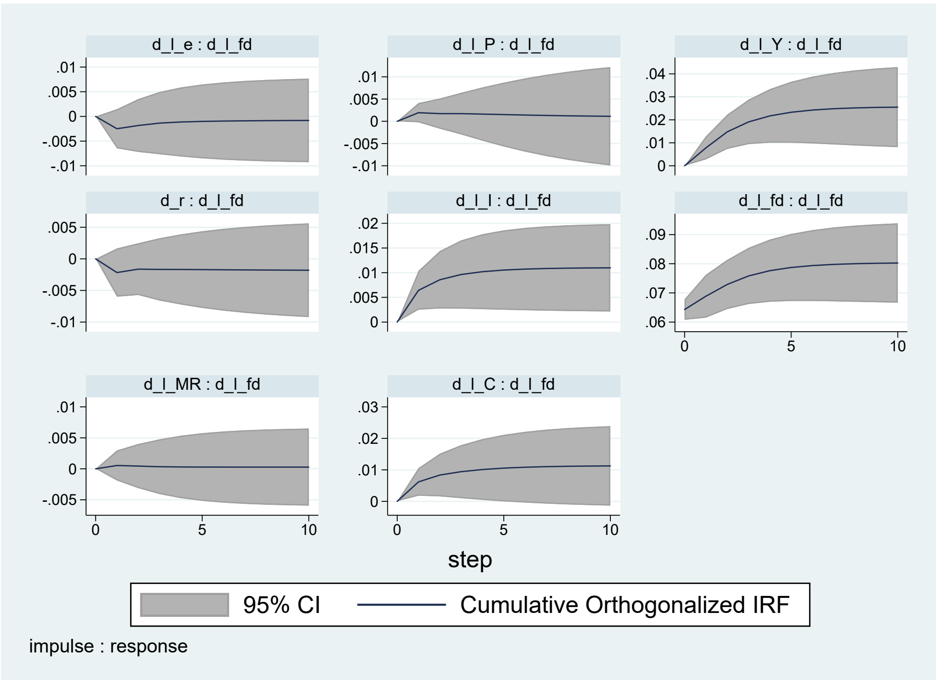


Table B.31: Granger causality tests - “Low” Doing Business Index

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.006	0.764	0.003	0.006	0.095	0.187	0.000
d_r	0.051	NA	0.003	0.000	0.809	0.937	0.358	0.002
d_l_MR	0.963	0.008	NA	0.000	0.093	0.592	0.255	0.062
d_l_P	0.004	0.000	0.000	NA	0.106	0.245	0.081	0.000
d_l_I	0.085	0.467	0.491	0.395	NA	0.808	0.957	0.095
d_l_C	0.854	0.754	0.960	0.948	0.342	NA	0.028	0.961
d_l_Y	0.644	0.529	0.044	0.546	0.000	0.001	NA	0.721
d_l_fd	0.033	0.277	0.059	0.052	0.117	0.496	0.049	NA
ALL	0.003	0.000	0.000	0.000	0.001	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.121: IRF - Impulse on Financial Development, “Low” Doing Business Index

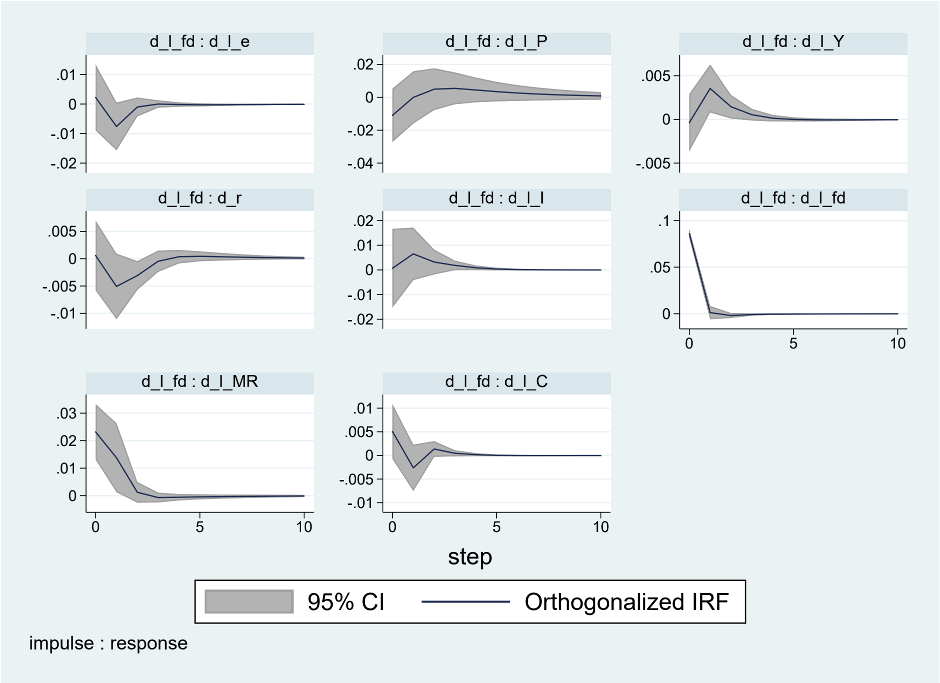


Figure B.122: Cumulative IRF - Impulse on Financial Development, “Low” Doing Business Index

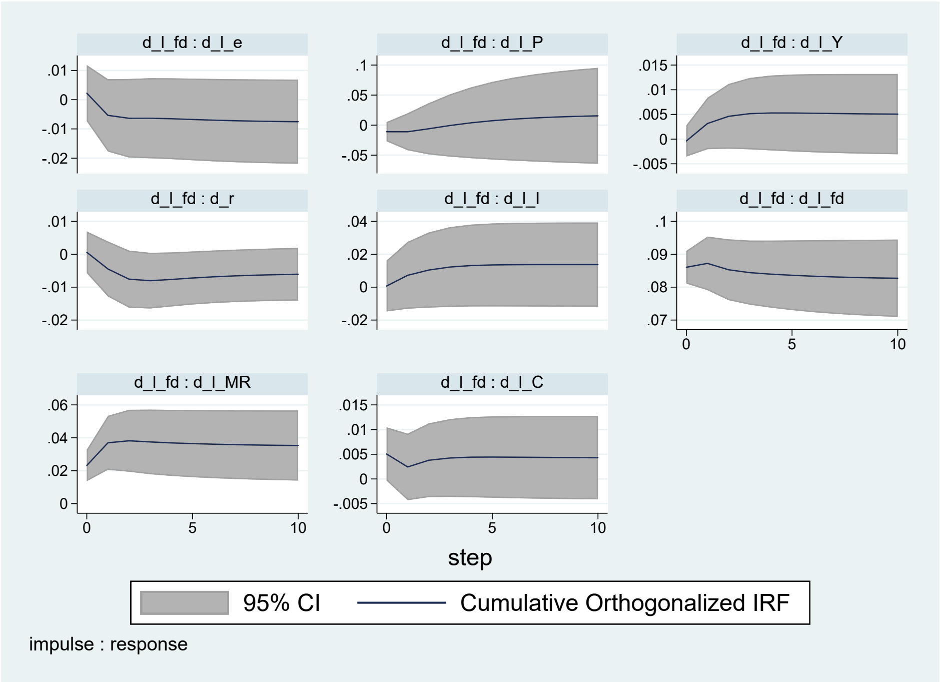


Figure B.123: IRF - Response of Financial Development, “Low” Doing Business Index

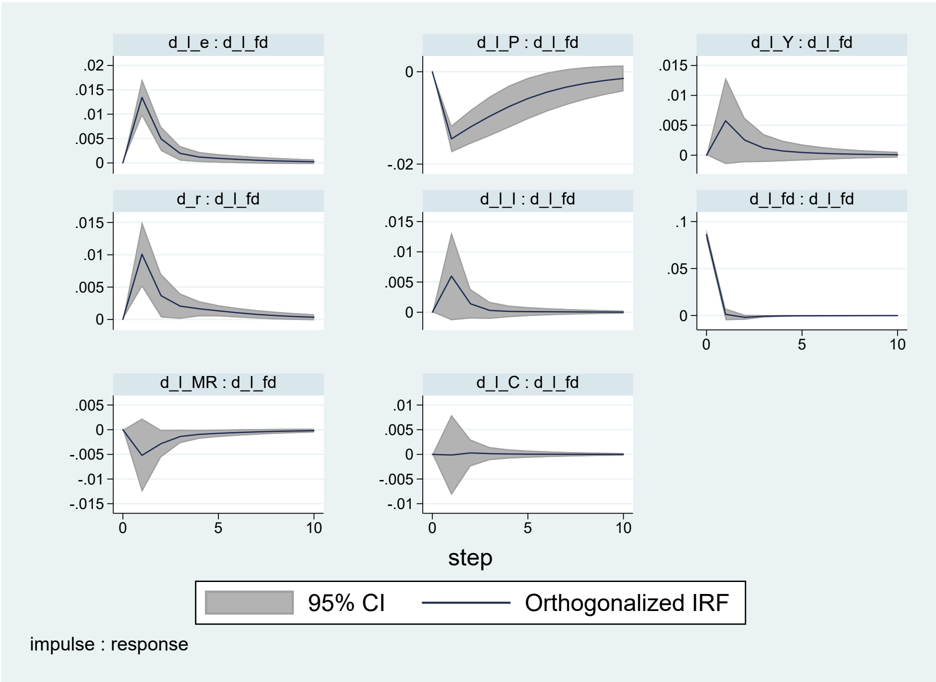
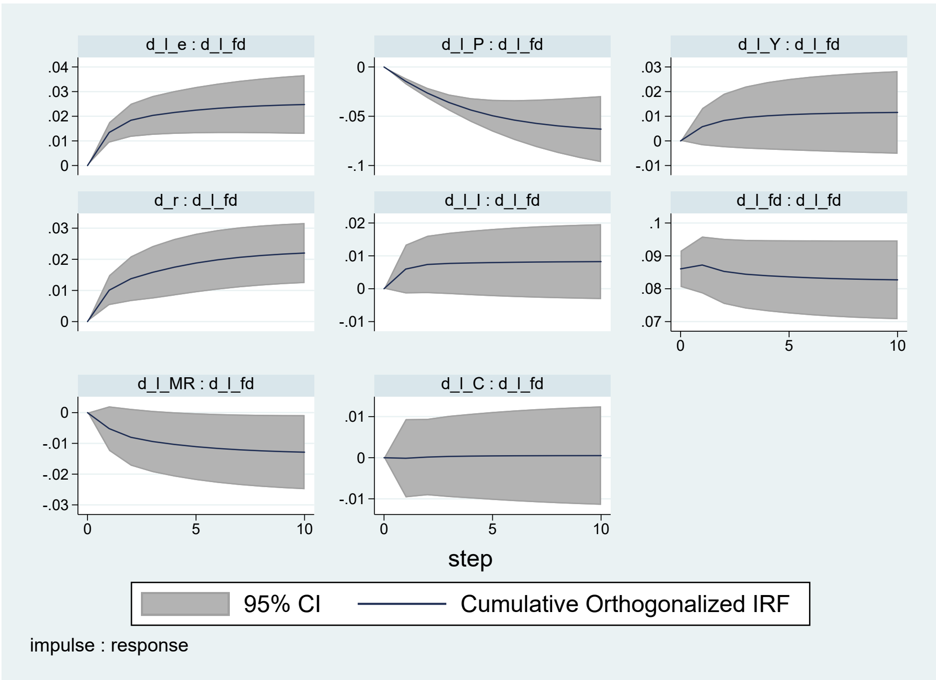


Figure B.124: Cumulative IRF - Response of Financial Development, “Low” Doing Business Index



B.10 Oil Prices

B.10.1 Brent

Table B.32: Granger causality tests - Brent

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.024	0.373	0.028	0.004	0.009	0.602	0.000
d_r	0.079	NA	0.004	0.000	0.444	0.799	0.085	0.201
d_l_MR	0.294	0.056	NA	0.019	0.257	0.501	0.527	0.207
d_l_P	0.005	0.000	0.000	NA	0.001	0.004	0.000	0.000
d_l_I	0.052	0.263	0.135	0.548	NA	0.849	0.718	0.021
d_l_C	0.301	0.650	0.588	0.834	0.113	NA	0.045	0.894
d_l_Y	0.853	0.908	0.060	0.400	0.000	0.000	NA	0.435
d_l_fd	0.135	0.535	0.272	0.152	0.001	0.592	0.000	NA
ALL	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.125: IRF - Impulse on Financial Development, Brent

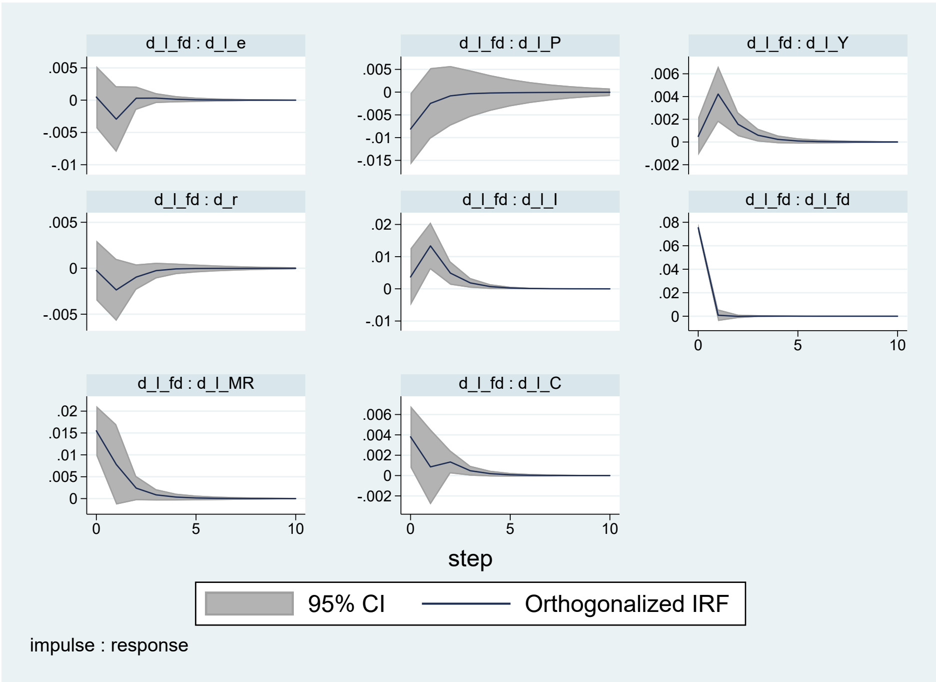


Figure B.126: Cumulative IRF - Impulse on Financial Development, Brent

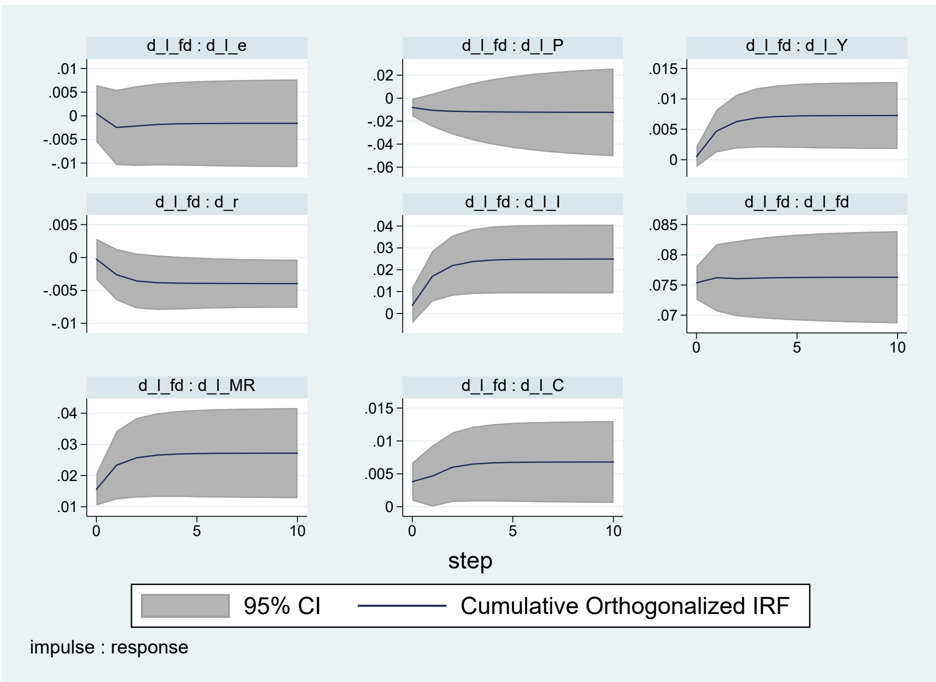


Figure B.127: IRF - Response of Financial Development, Brent

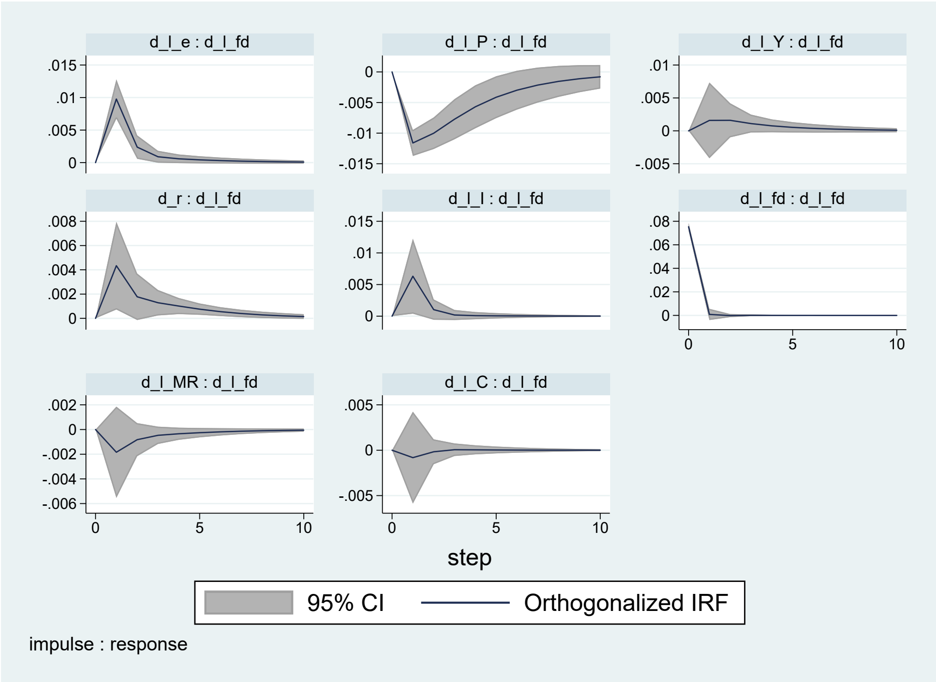


Figure B.128: Cumulative IRF - Response of Financial Development, Brent

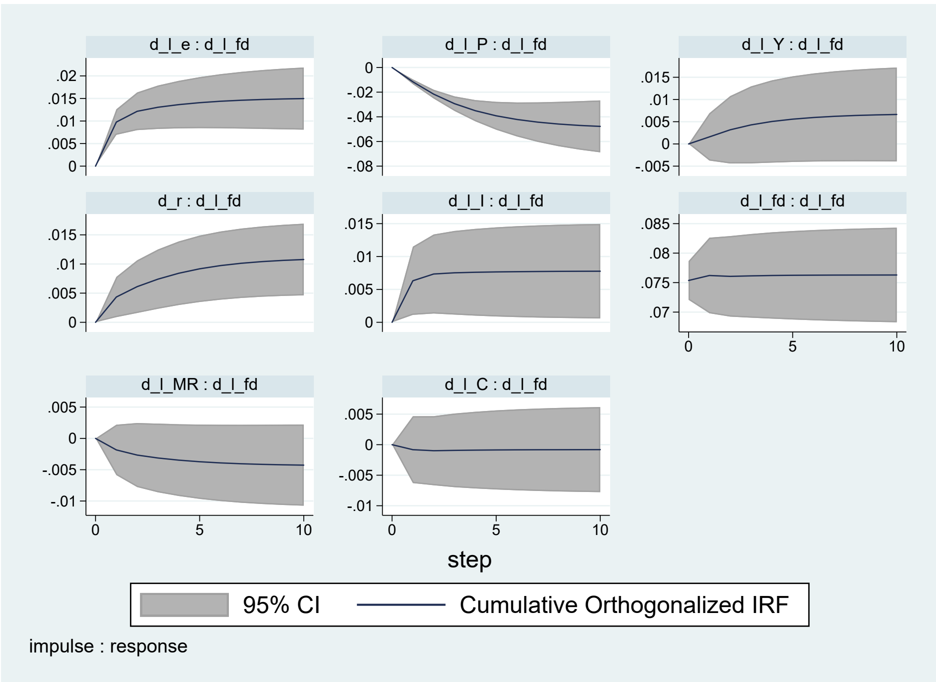


Table B.33: Granger causality tests - Brent, "High" Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.023	0.101	0.003	0.001	0.007	0.649	0.755
d_r	0.701	NA	0.294	0.000	0.455	0.771	0.659	0.033
d_l_MR	1.000	0.732	NA	0.787	0.186	0.368	0.655	0.241
d_l_P	0.181	0.000	0.001	NA	0.020	0.044	0.009	0.000
d_l_I	0.566	0.015	0.009	0.933	NA	0.070	0.057	0.000
d_l_C	0.795	0.994	0.814	0.075	0.002	NA	0.638	0.192
d_l_Y	0.015	0.549	0.768	0.428	0.001	0.436	NA	0.001
d_l_fd	0.988	0.271	0.495	0.224	0.000	0.089	0.000	NA
ALL	0.140	0.000	0.000	0.000	0.000	0.001	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.129: IRF - Impulse on Financial Development, Brent, “High” Financial Development

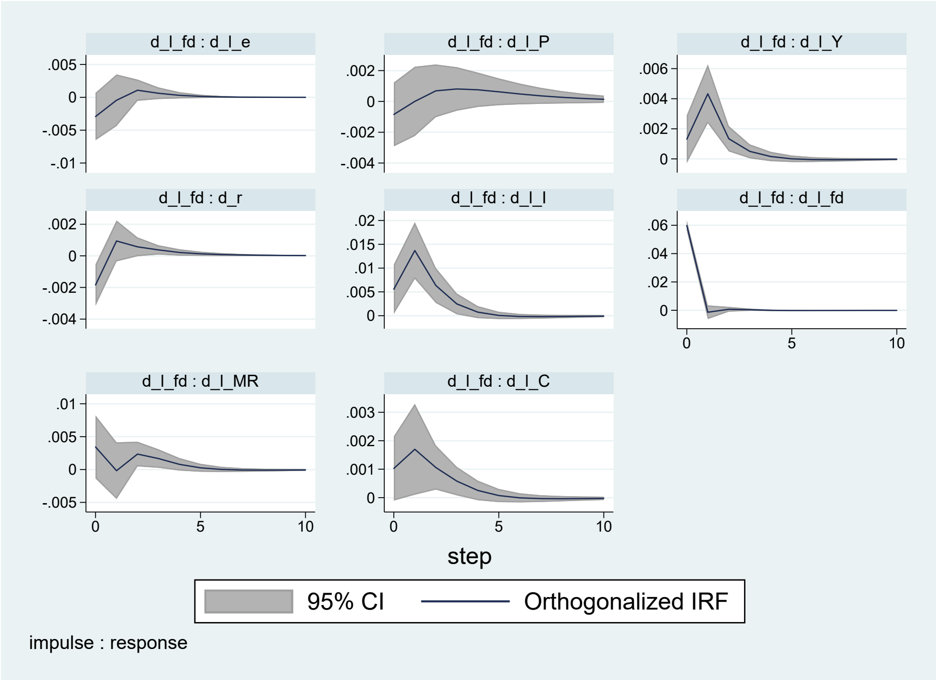


Figure B.130: Cumulative IRF - Impulse on Financial Development, Brent, “High” Financial Development

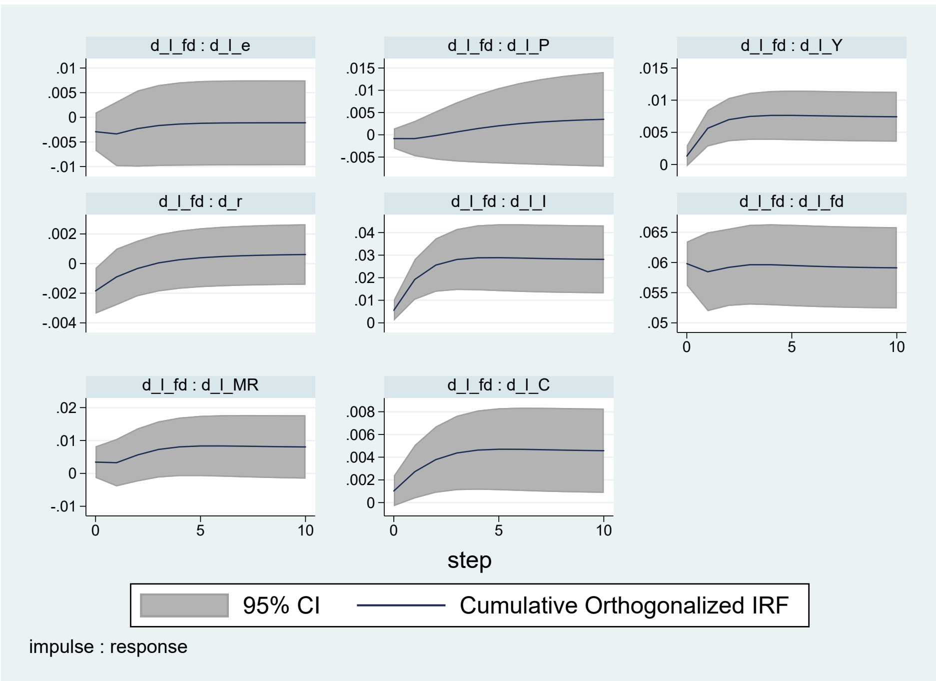


Figure B.131: IRF - Response of Financial Development, Brent, “High” Financial Development

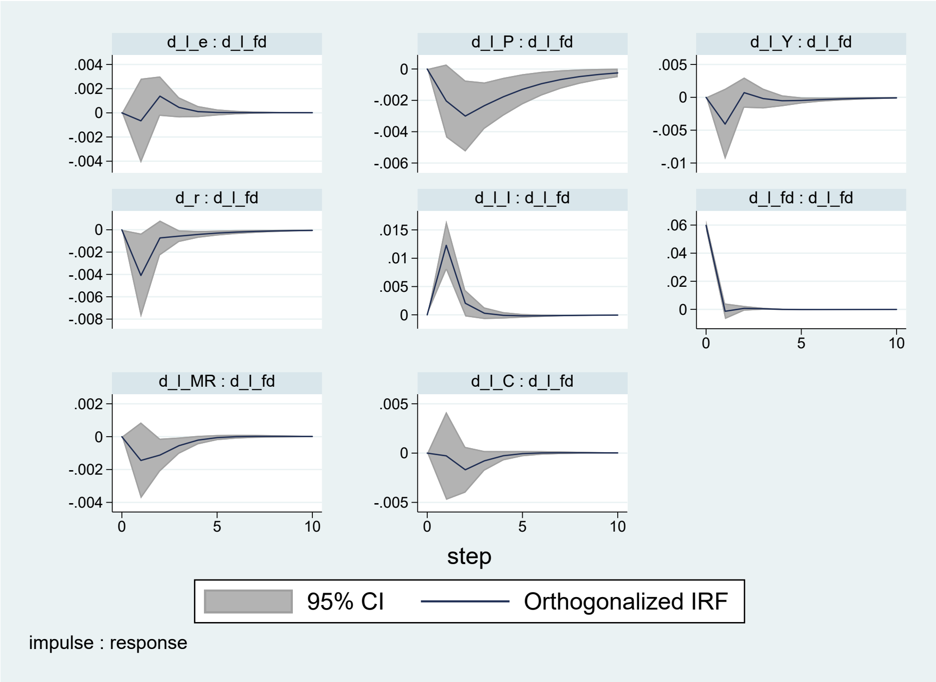


Figure B.132: Cumulative IRF - Response of Financial Development, Brent, “High” Financial Development

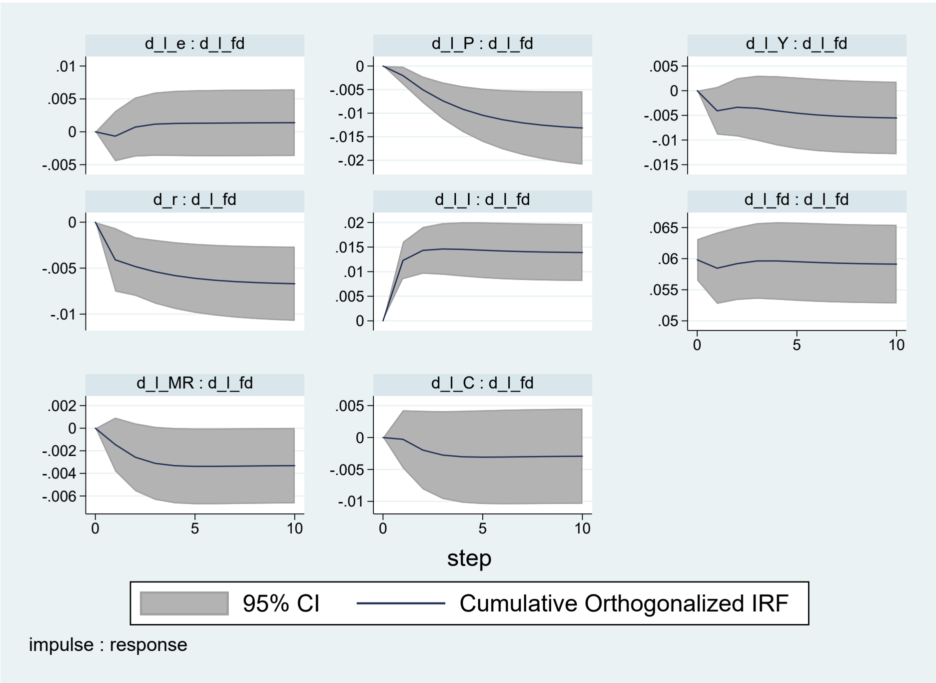


Table B.34: Granger causality tests - Brent, "Low" Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.108	0.287	0.110	0.000	0.155	0.790	0.000
d_r	0.093	NA	0.000	0.000	0.639	0.506	0.221	0.002
d_l_MR	0.931	0.008	NA	0.000	0.202	0.811	0.210	0.184
d_l_P	0.000	0.000	0.000	NA	0.000	0.366	0.000	0.000
d_l_I	0.077	0.711	0.553	0.719	NA	0.728	0.941	0.119
d_l_C	0.845	0.991	0.871	0.541	0.277	NA	0.010	0.815
d_l_Y	0.332	0.533	0.055	0.090	0.000	0.006	NA	0.516
d_l_fd	0.065	0.372	0.059	0.287	0.118	0.929	0.131	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.133: IRF - Impulse on Financial Development, Brent, “Low” Financial Development

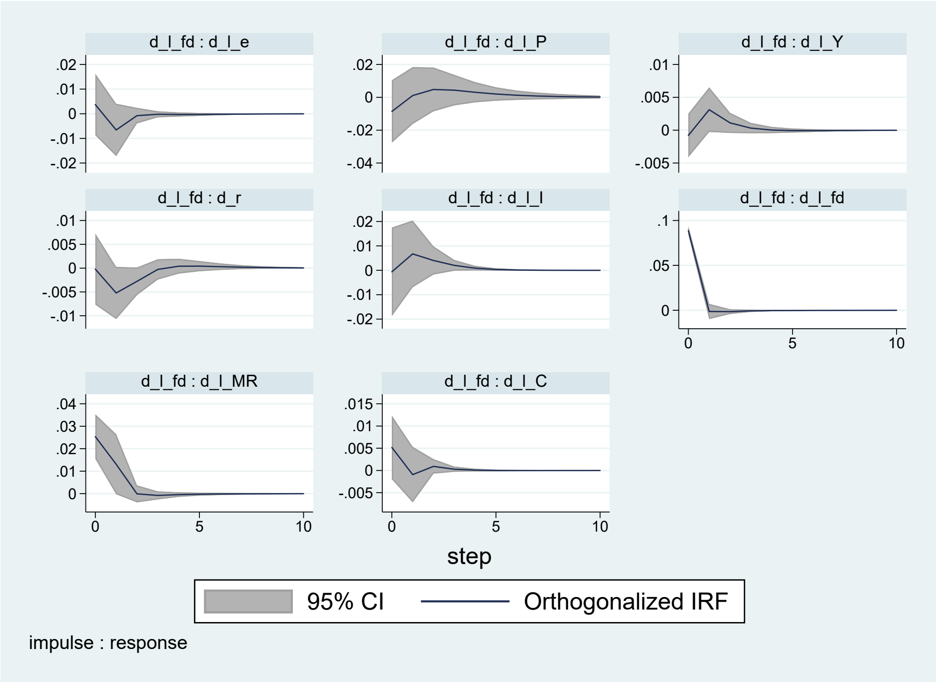


Figure B.134: Cumulative IRF - Impulse on Financial Development, Brent, “Low” Financial Development

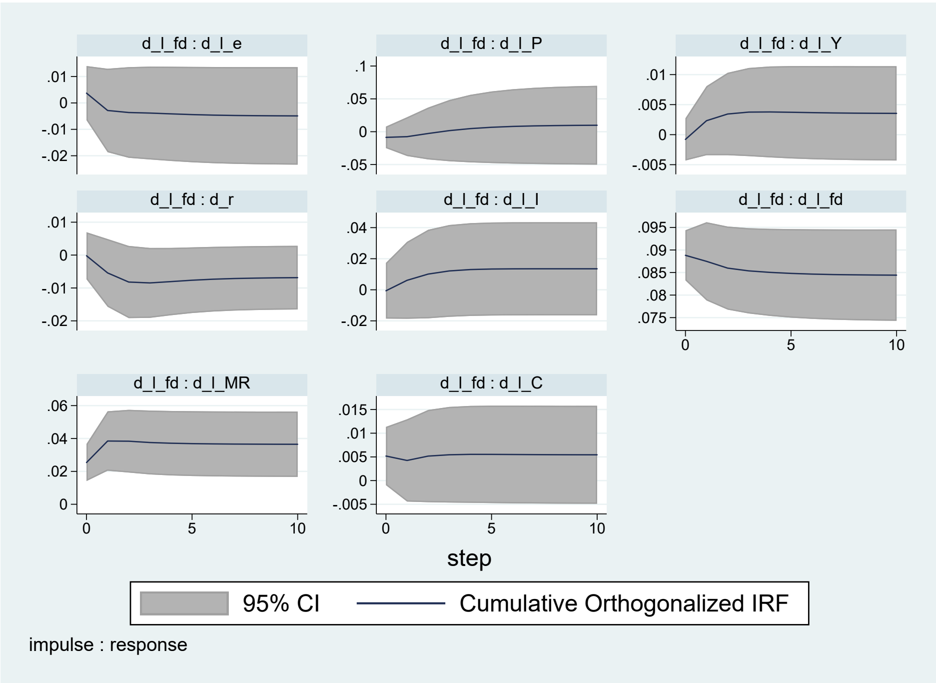


Figure B.135: IRF - Response of Financial Development, Brent, “Low” Financial Development

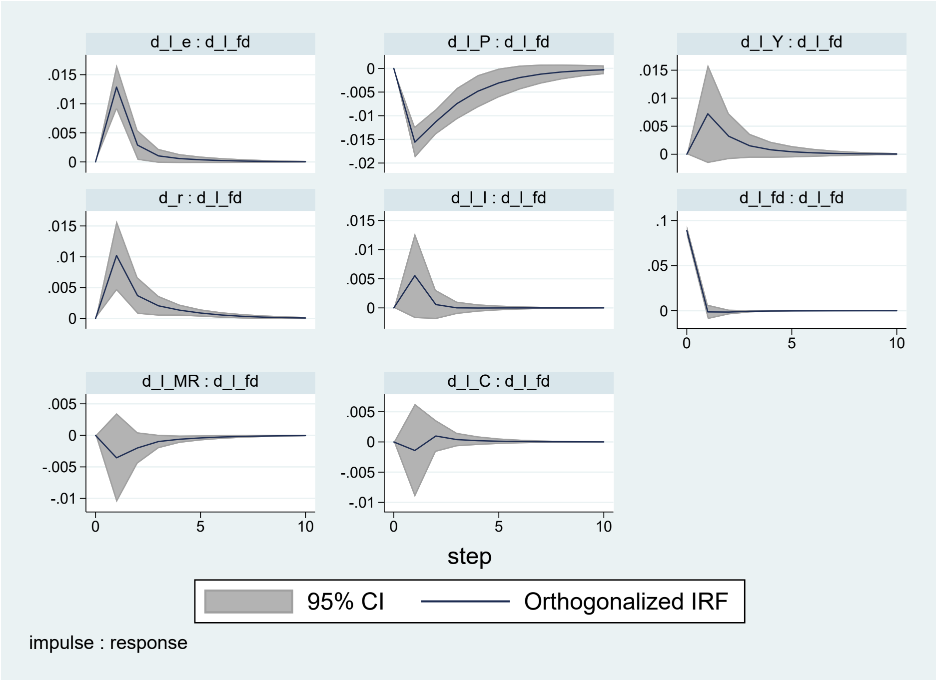
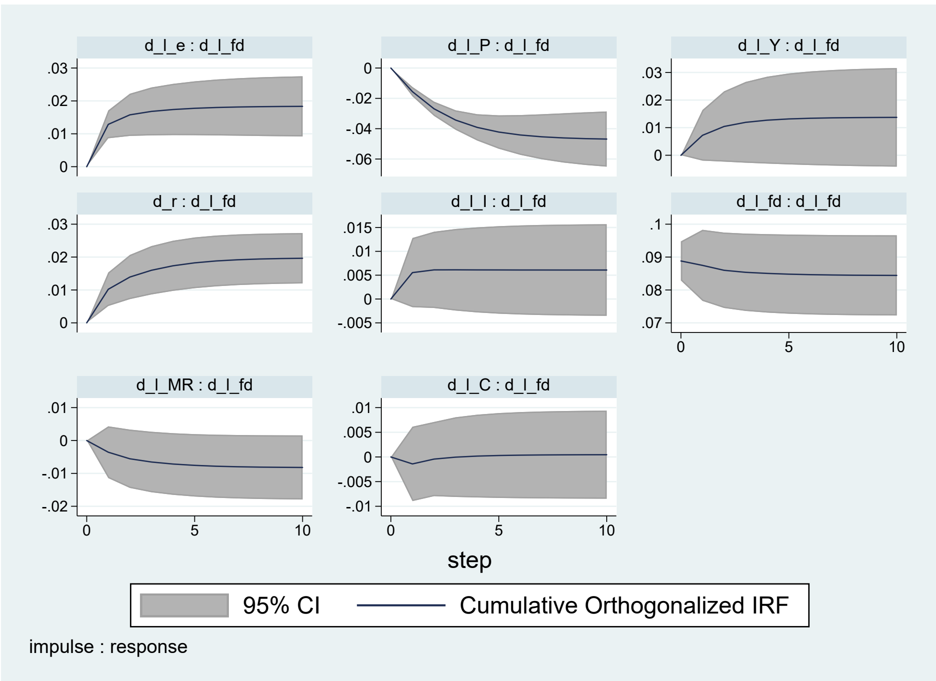


Figure B.136: Cumulative IRF - Response of Financial Development, Brent, “Low” Financial Development



B.10.2 WTI

Table B.35: Granger causality tests - WTI

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.023	0.364	0.027	0.004	0.008	0.660	0.000
d_r	0.073	NA	0.004	0.000	0.454	0.801	0.076	0.227
d_l_MR	0.293	0.052	NA	0.018	0.248	0.489	0.521	0.216
d_l_P	0.005	0.000	0.000	NA	0.001	0.004	0.000	0.000
d_l_I	0.053	0.269	0.135	0.577	NA	0.851	0.713	0.021
d_l_C	0.310	0.640	0.579	0.808	0.112	NA	0.044	0.894
d_l_Y	0.862	0.942	0.056	0.346	0.000	0.000	NA	0.431
d_l_fd	0.138	0.522	0.267	0.147	0.001	0.594	0.000	NA
ALL	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.137: IRF - Impulse on Financial Development, WTI

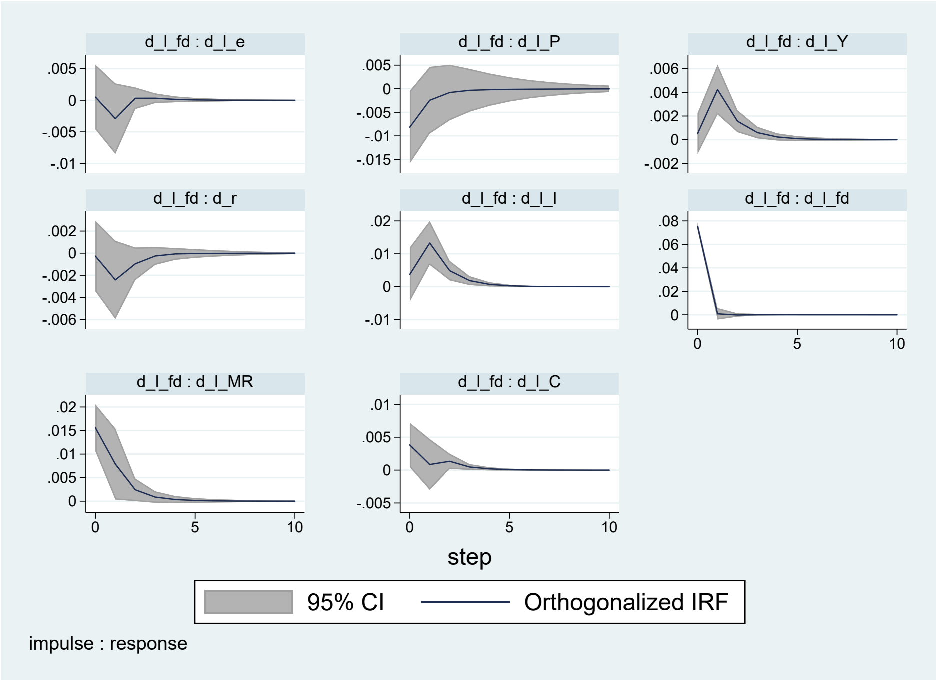


Figure B.138: Cumulative IRF - Impulse on Financial Development, WTI

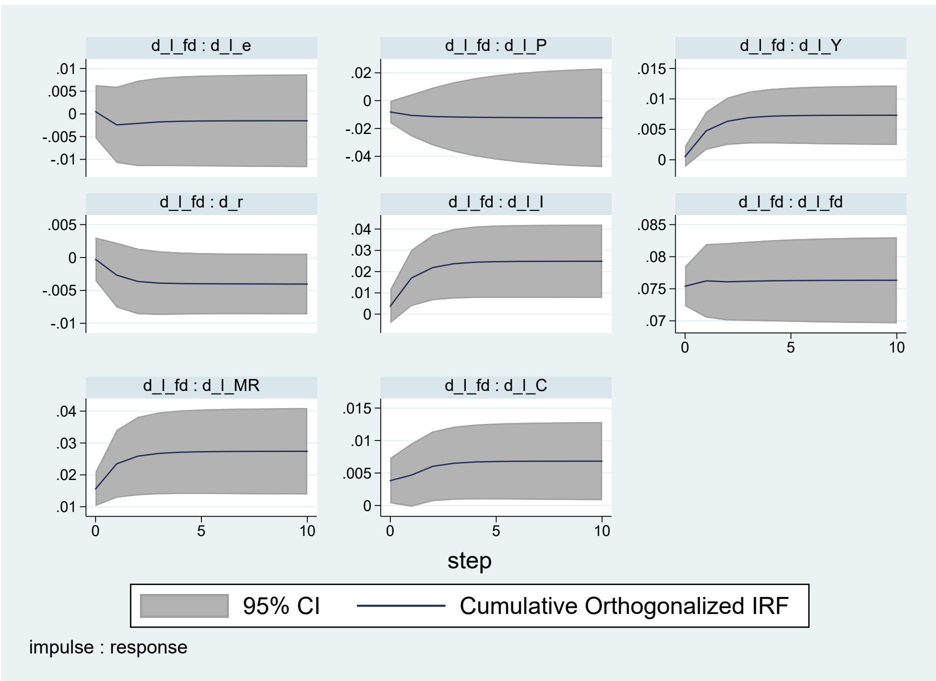


Figure B.139: IRF - Response of Financial Development, WTI

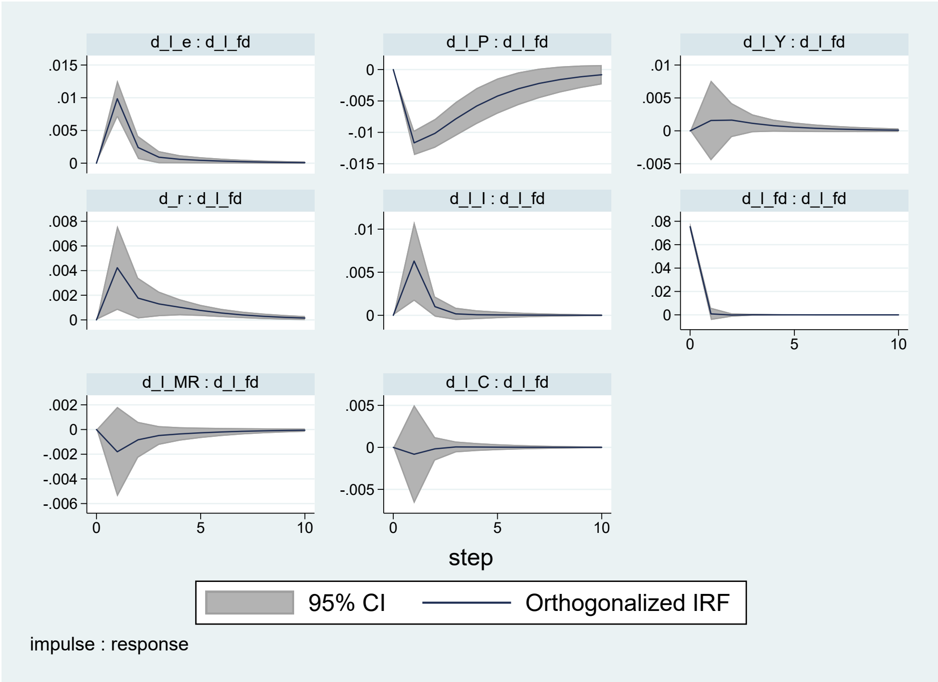


Figure B.140: Cumulative IRF - Response of Financial Development, WTI

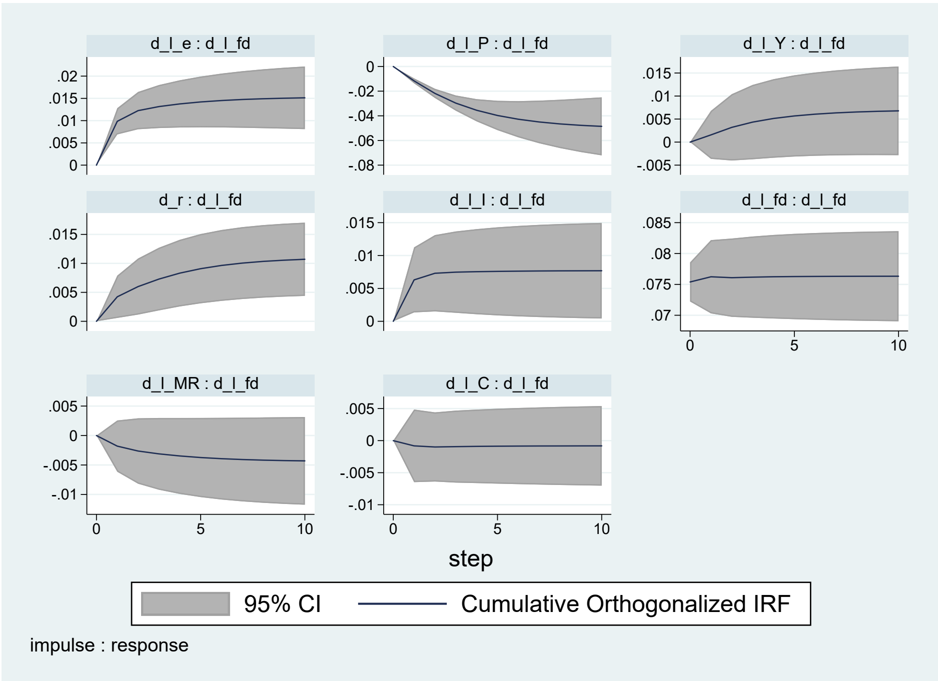


Table B.36: Granger causality tests - WTI, “High” Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.022	0.104	0.003	0.001	0.007	0.645	0.778
d_r	0.670	NA	0.301	0.000	0.421	0.765	0.669	0.034
d_l_MR	0.989	0.685	NA	0.827	0.201	0.324	0.701	0.282
d_l_P	0.173	0.000	0.001	NA	0.017	0.034	0.006	0.000
d_l_I	0.569	0.016	0.010	0.955	NA	0.075	0.060	0.000
d_l_C	0.767	0.988	0.852	0.061	0.002	NA	0.672	0.169
d_l_Y	0.015	0.533	0.792	0.415	0.001	0.479	NA	0.001
d_l_fd	0.999	0.273	0.475	0.196	0.000	0.108	0.000	NA
ALL	0.146	0.000	0.000	0.000	0.000	0.001	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.141: IRF - Impulse on Financial Development, WTI, “High” Financial Development

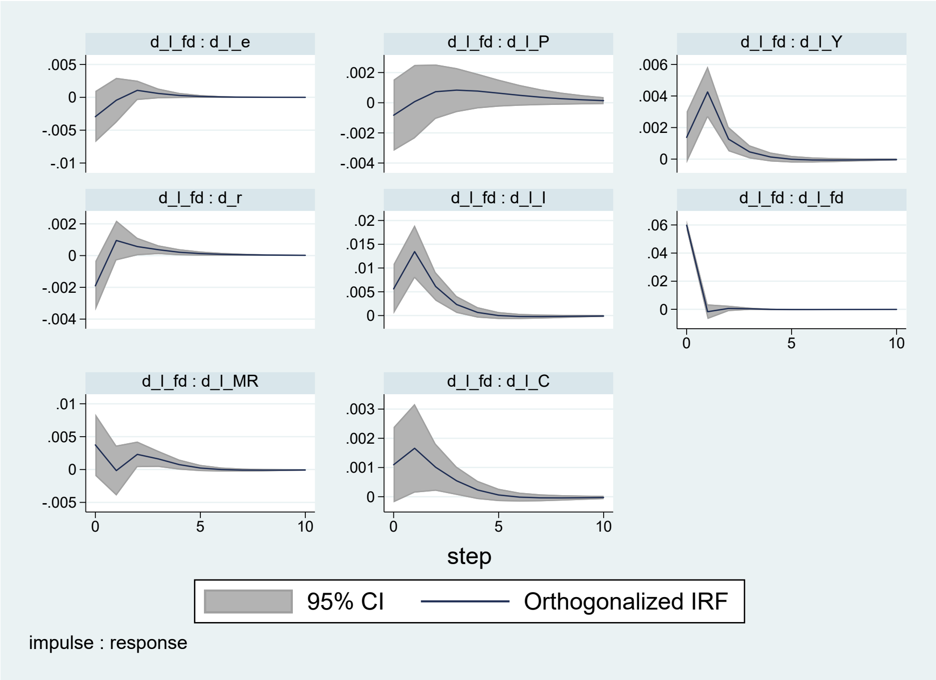


Figure B.142: Cumulative IRF - Impulse on Financial Development, WTI, “High” Financial Development

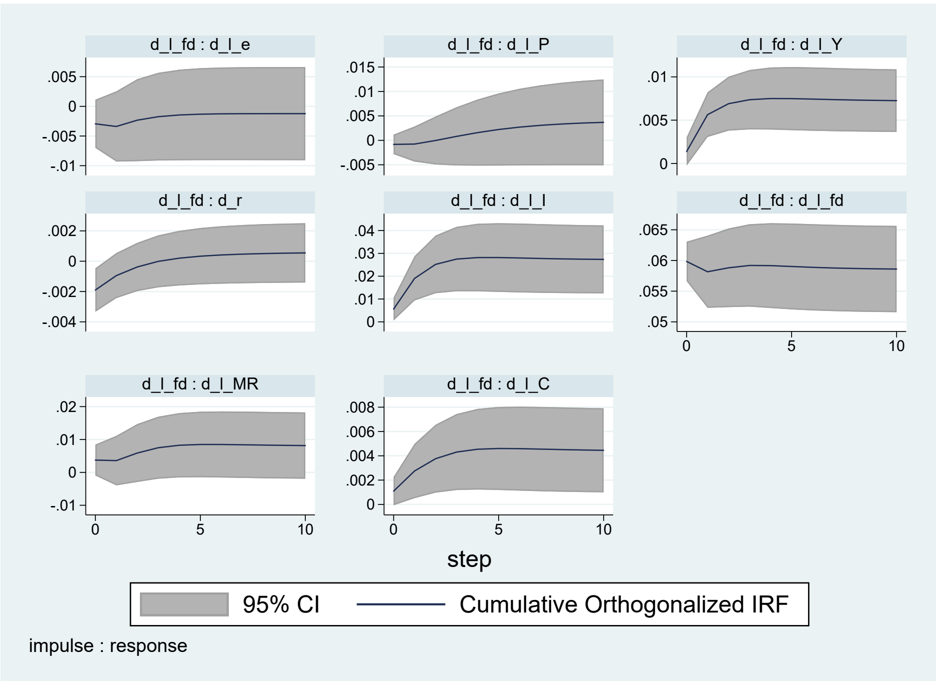


Figure B.143: IRF - Response of Financial Development, WTI, “High” Financial Development

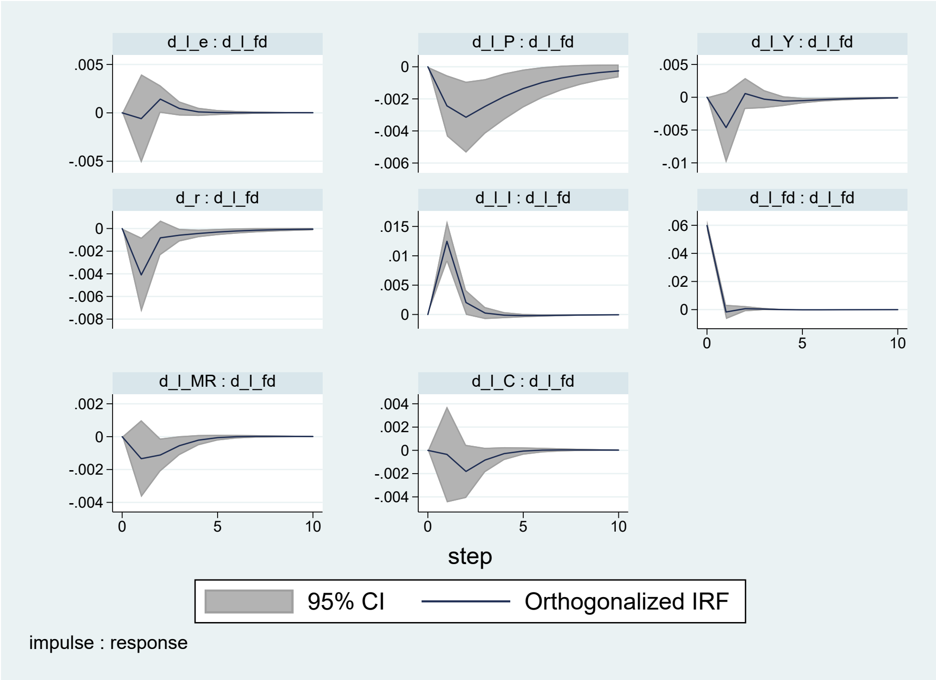


Figure B.144: Cumulative IRF - Response of Financial Development, WTI, “High” Financial Development

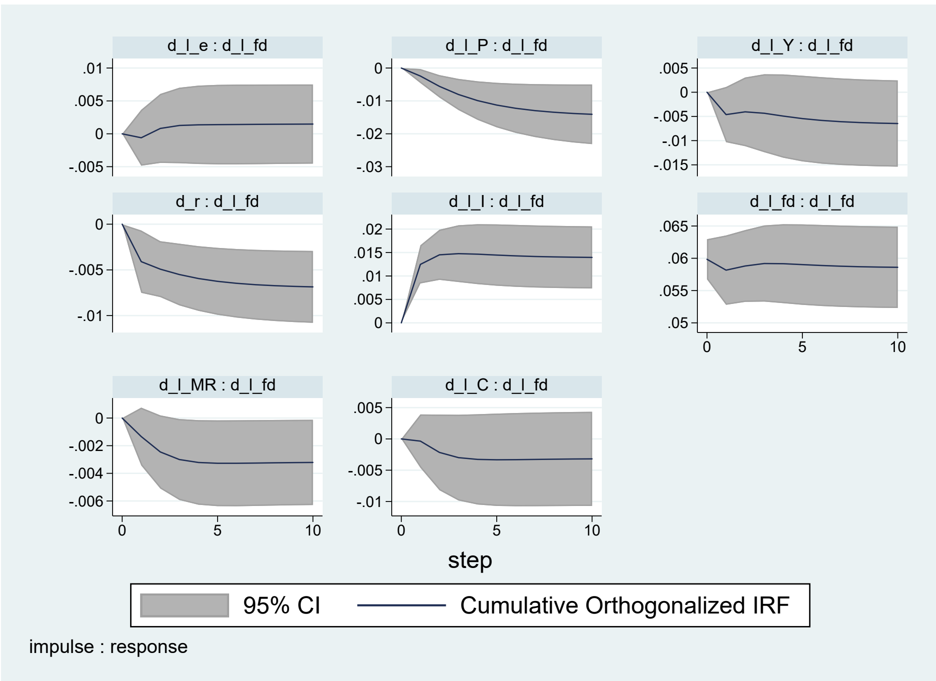


Table B.37: Granger causality tests - WTI, “Low” Financial Development

	d_l_e	d_r	d_l_MR	d_l_P	d_l_I	d_l_C	d_l_Y	d_l_fd
d_l_e	NA	0.105	0.284	0.107	0.000	0.164	0.812	0.000
d_r	0.088	NA	0.000	0.000	0.623	0.497	0.212	0.002
d_l_MR	0.942	0.008	NA	0.000	0.198	0.811	0.214	0.184
d_l_P	0.000	0.000	0.000	NA	0.000	0.402	0.000	0.000
d_l_I	0.078	0.725	0.561	0.753	NA	0.734	0.938	0.122
d_l_C	0.863	0.971	0.863	0.569	0.278	NA	0.010	0.809
d_l_Y	0.343	0.559	0.047	0.074	0.000	0.006	NA	0.489
d_l_fd	0.067	0.368	0.056	0.277	0.126	0.929	0.128	NA
ALL	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000

Notes: The table shows the p-values for the Granger causality tests of the hypotheses that the variables in the rows Granger-cause the variables in the columns. For example, the cell corresponding to row d_r and column d_l_P gives the p-value of the test that the interest rate Granger-causes inflation.

Figure B.145: IRF - Impulse on Financial Development, WTI, “Low” Financial Development

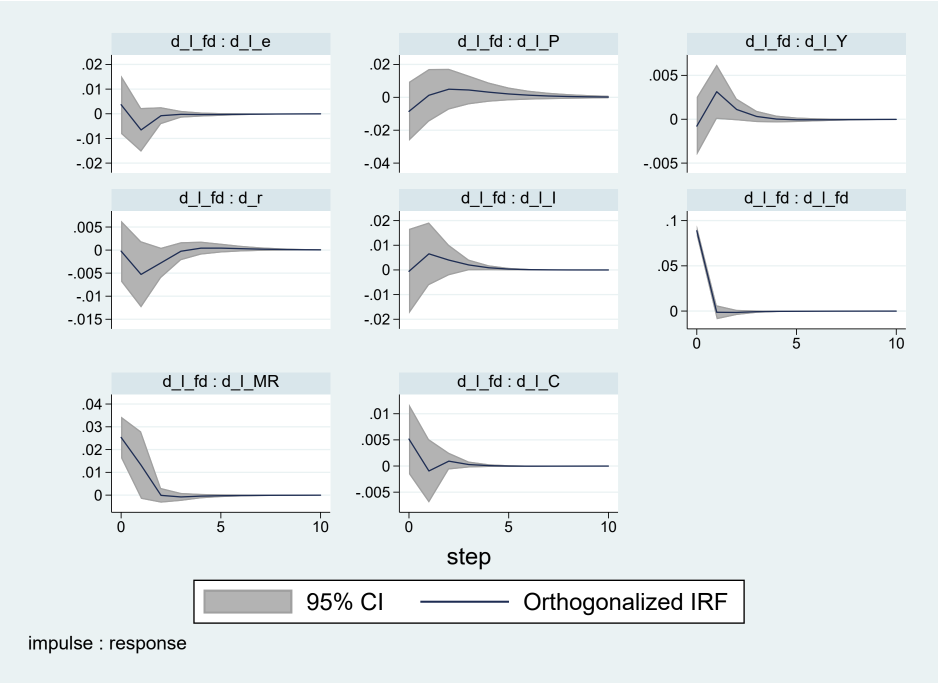


Figure B.146: Cumulative IRF - Impulse on Financial Development, WTI, “Low” Financial Development

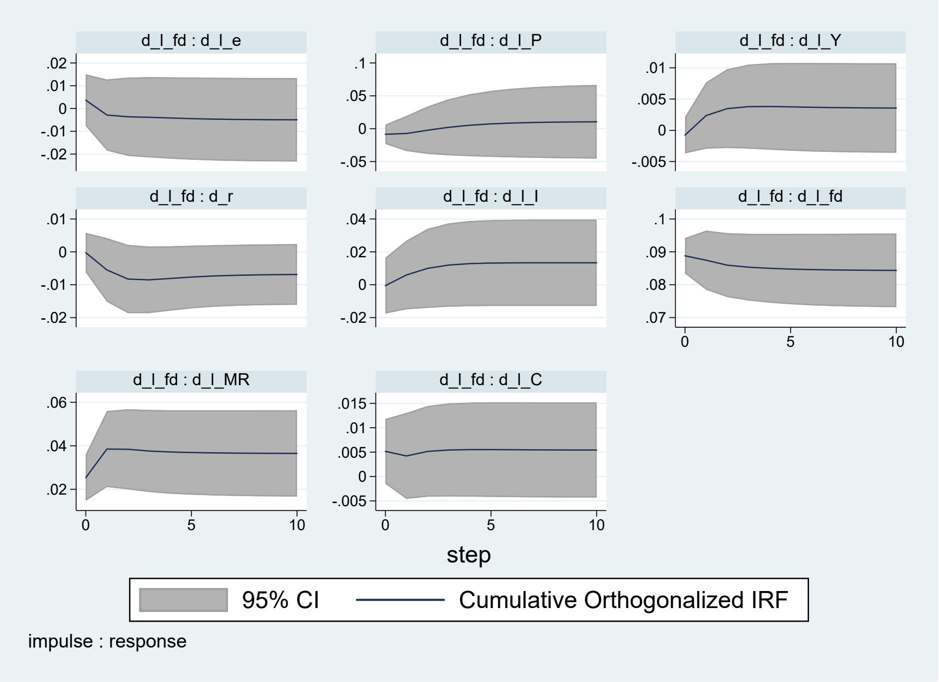


Figure B.147: IRF - Response of Financial Development, WTI, “Low” Financial Development

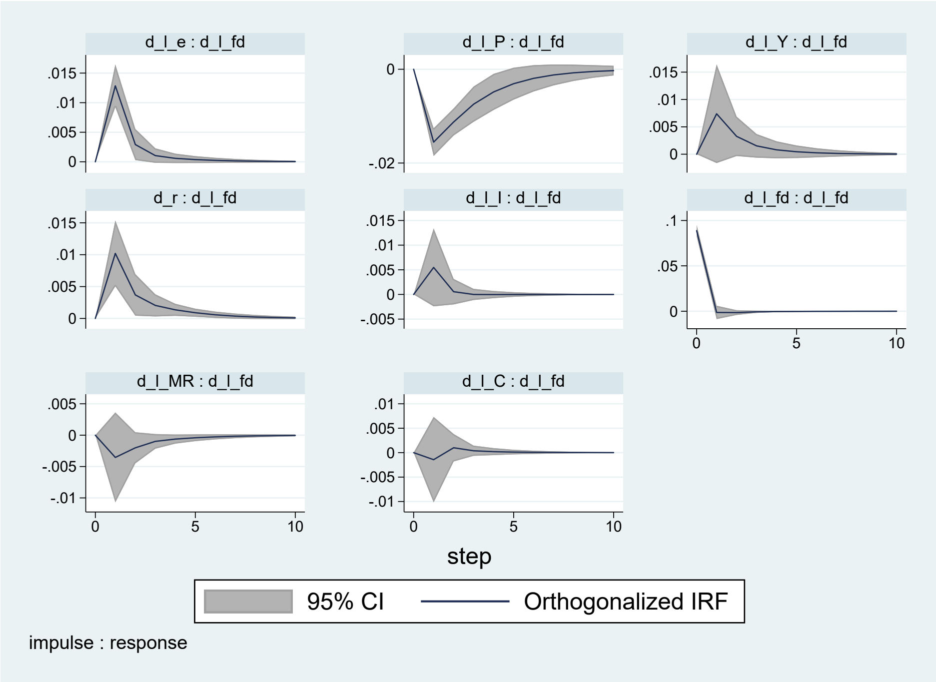
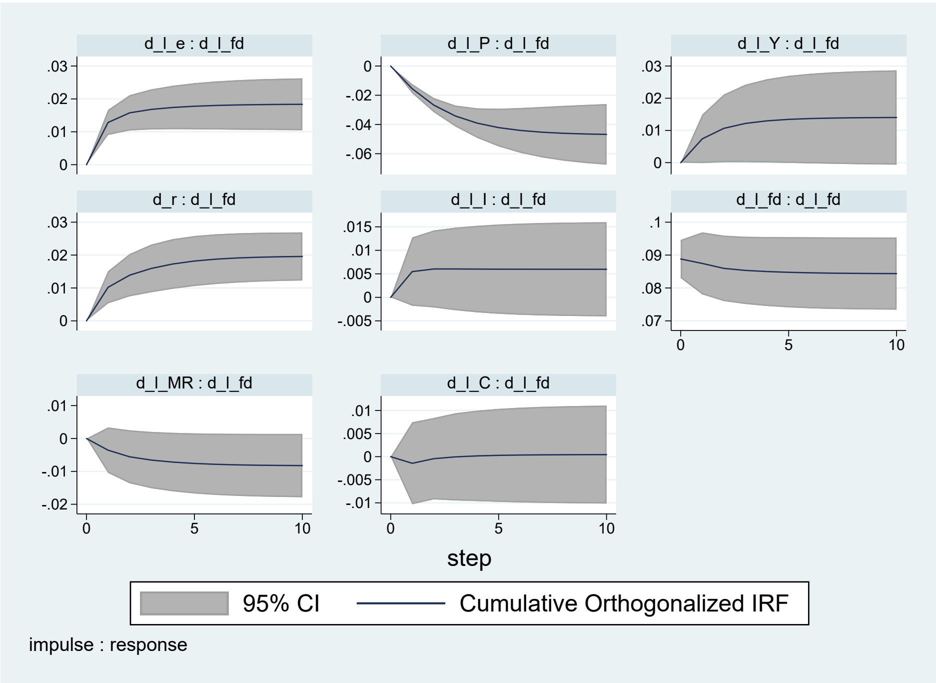


Figure B.148: Cumulative IRF - Response of Financial Development, WTI, “Low” Financial Development



Appendix C

Financial Development and Consumption Adjustment under Smooth Transition

C.1 Transition and Coefficient Plots

Figure C.1: Transition Plot

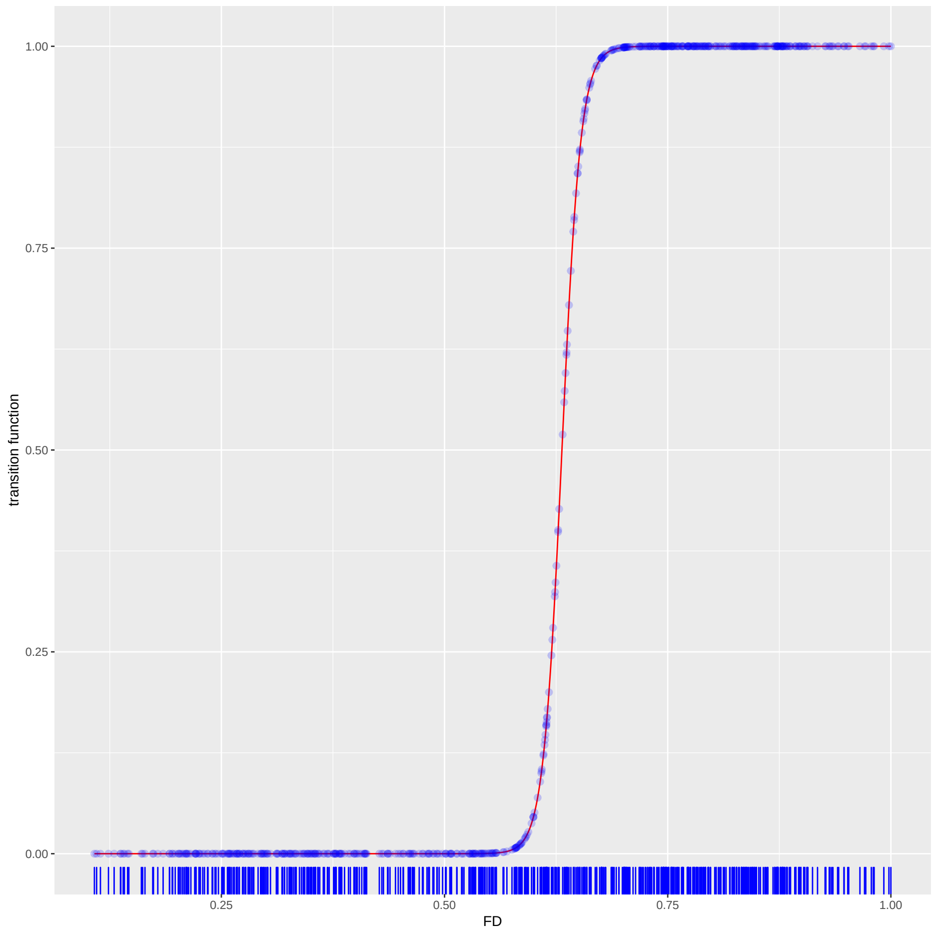


Figure C.2: β_y as Financial Development changes

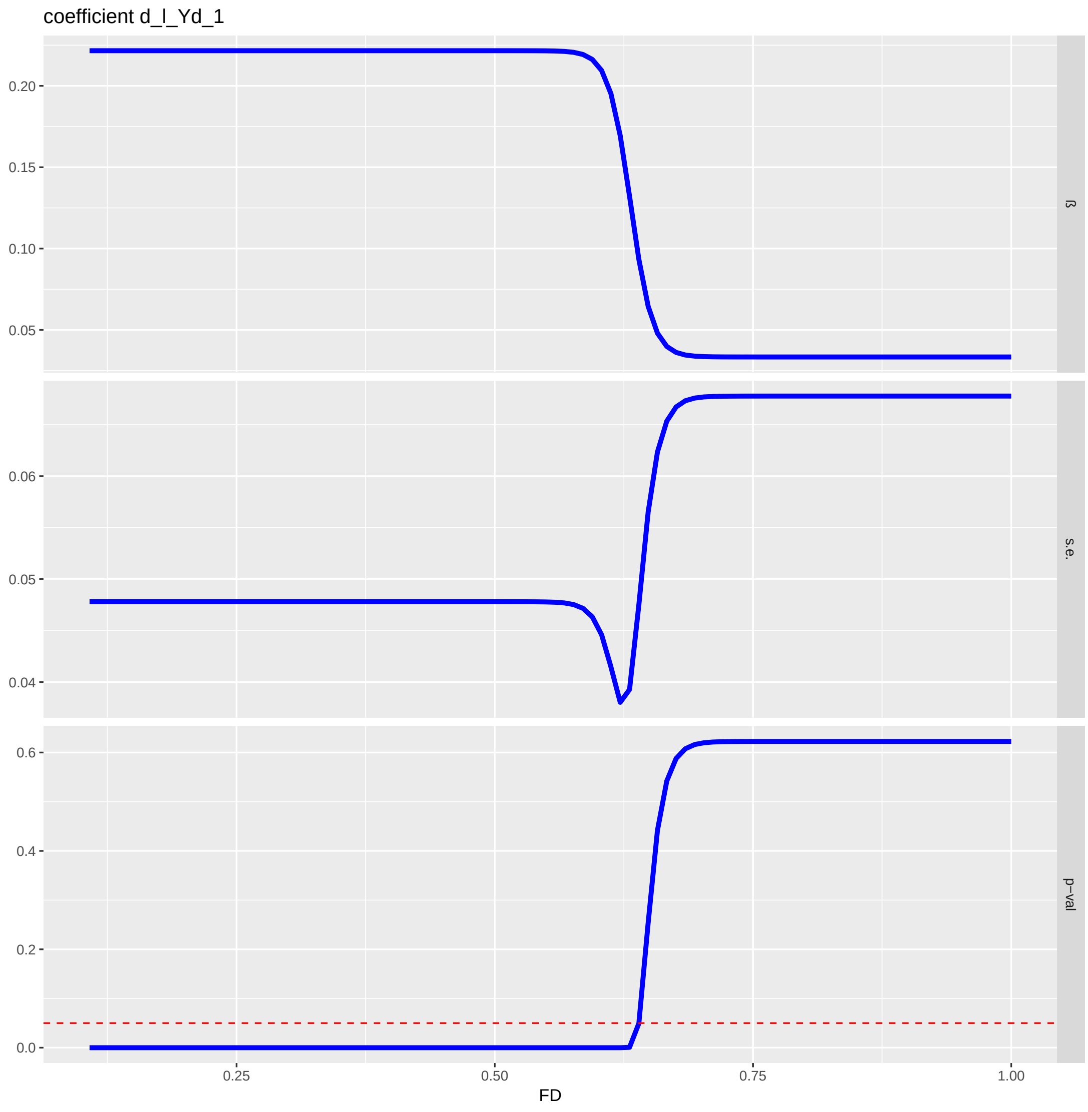


Figure C.3: β_r as Financial Development changes

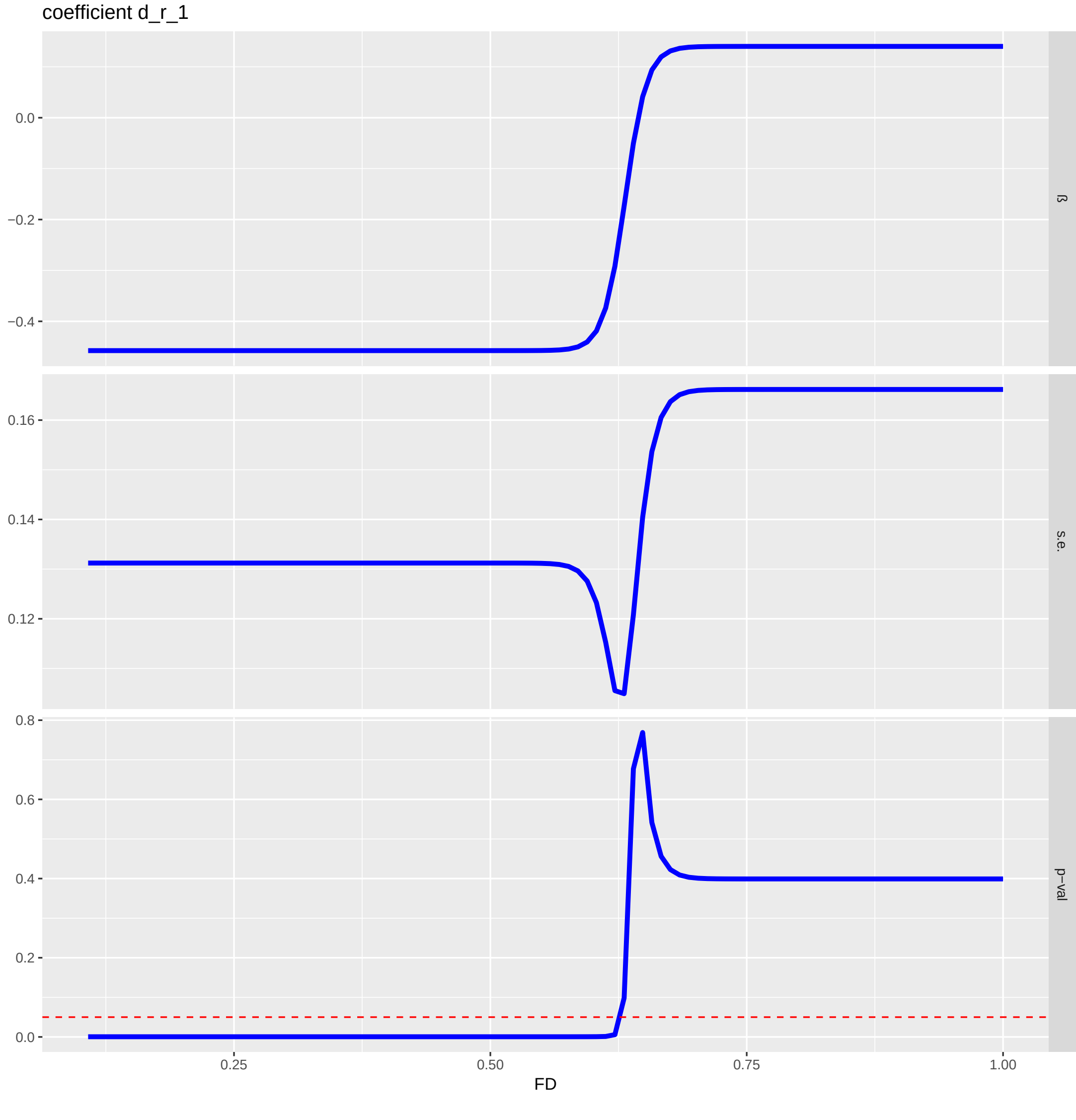


Figure C.4: β_w as Financial Development changes

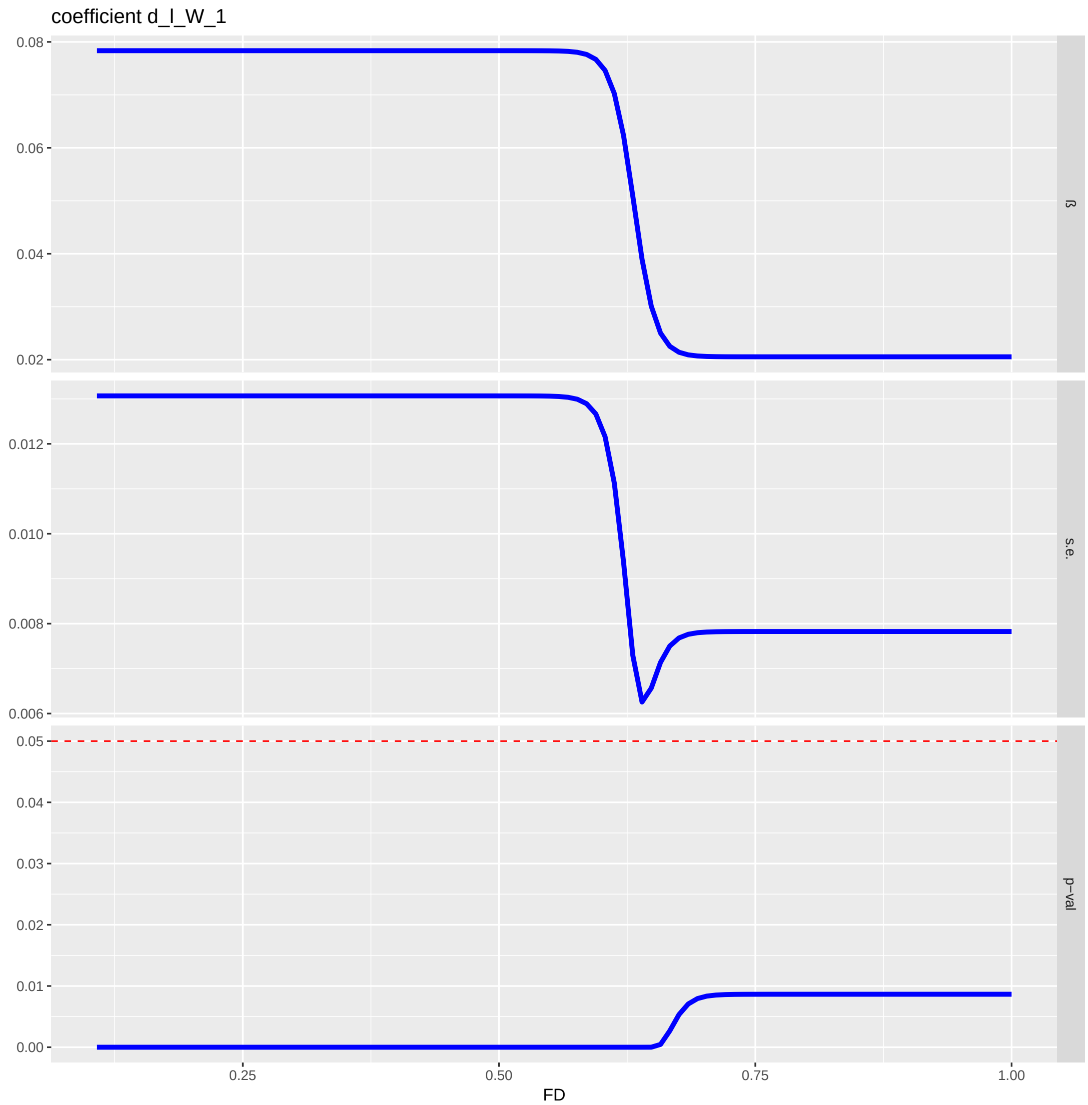
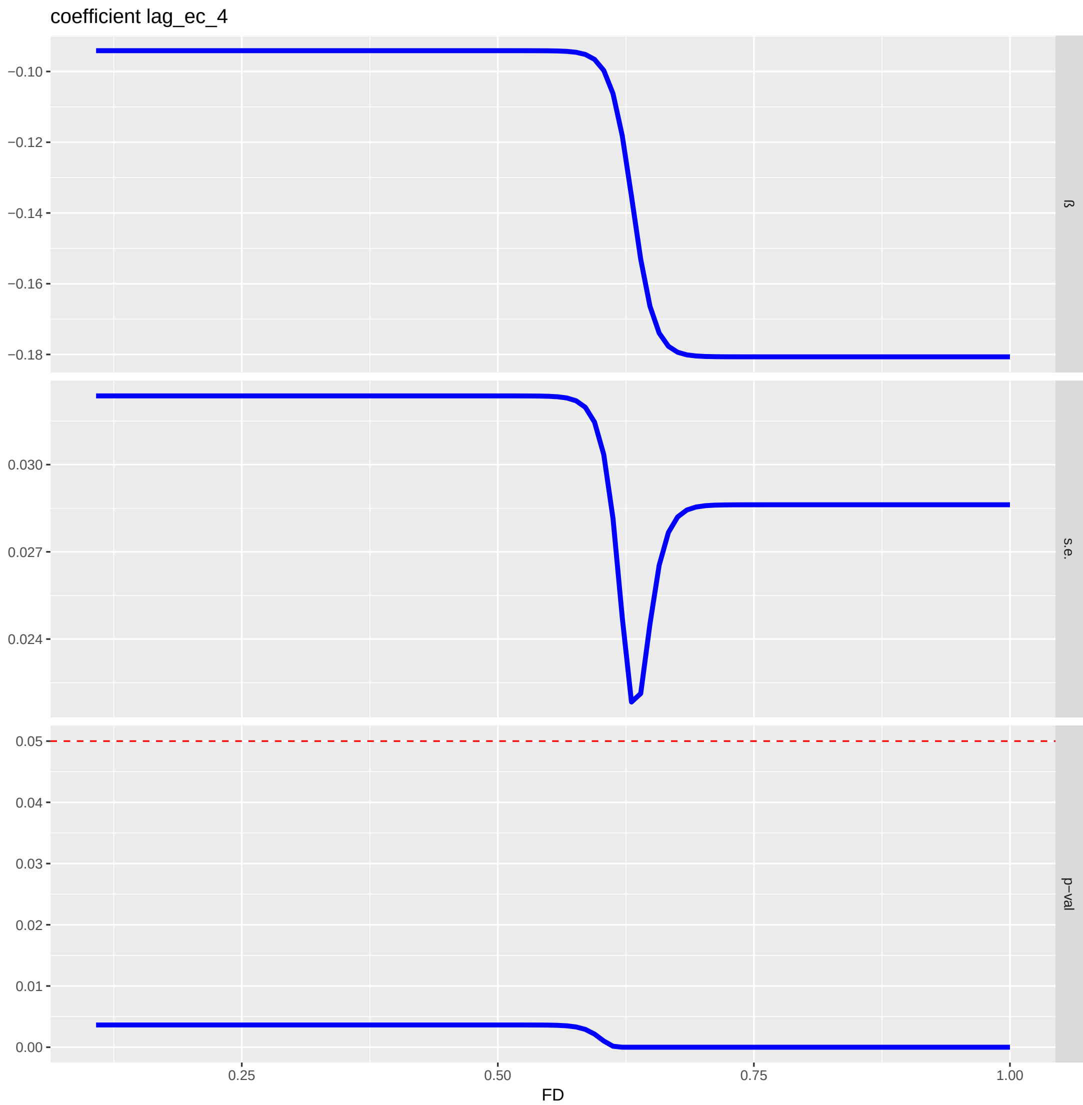


Figure C.5: λ as Financial Development changes



C.2 Additional Variables

Table C.1: ECM Regression Results - Additional Variables

	(i)	(ii)	(iii)
$\Delta \log Y_{i,t-1}$	0.207***	0.207***	0.166***
	(0.038)	(0.04)	(0.042)
$\Delta r_{i,t-1}$	-0.38***	-0.417***	-0.409***
	(0.133)	(0.121)	(0.123)
$\Delta \log W_{i,t-1}$	0.053***	0.06***	0.057***
	(0.01)	(0.009)	(0.009)
$z_{i,t-1}$	-0.107***	-0.111***	-0.113***
	(0.032)	(0.031)	(0.03)
$\Delta \log P_{i,t-1}$	-0.171		
	(0.109)		
$\Delta Cred_{i,t-1}$		0.041*	
		(0.025)	
$\Delta UR_{i,t-1}$			-0.375**
			(0.174)
R^2	0.45197	0.45028	0.45292

Notes: P is the price level, $Cred$ is a credit measure and UR is the unemployment rate

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Linearity Tests - Additional Regressors

	LM_{χ}	p-value
(i)	11.36	0.04466
(ii)	11.09	0.04965
(iii)	7.89	0.1624

Table C.3: Smooth Transition Panel ECM Regression Results, Base Regime - Additional Variables

	(i)	(ii)	(iii)
$\Delta \log Y_{i,t-1}$	0.228***	0.222***	0.198***
	(0.044)	(0.046)	(0.047)
$\Delta r_{i,t-1}$	-0.455***	-0.457***	-0.46***
	(0.133)	(0.13)	(0.13)
$\Delta \log W_{i,t-1}$	0.067***	0.078***	0.074***
	(0.014)	(0.013)	(0.014)
$z_{i,t-1}$	-0.092***	-0.095***	-0.097***
	(0.033)	(0.032)	(0.032)
$\Delta \log P_{i,t-1}$	-0.178		
	(0.118)		
$\Delta Cred_{i,t-1}$		-0.004	
		(0.04)	
$\Delta UR_{i,t-1}$			-0.249
			(0.213)

Notes: P is the price level, $Cred$ is a credit measure and UR is the unemployment rate

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Smooth Transition Panel ECM Regression Results, Nonlinear Part - Additional Variables

	(i)	(ii)	(iii)
$\Delta \log Y_{i,t-1}$	-0.212**	-0.179**	-0.198***
	(0.088)	(0.083)	(0.076)
$\Delta r_{i,t-1}$	0.628***	0.502***	0.426
	(0.213)	(0.171)	(0.265)
$\Delta \log W_{i,t-1}$	-0.047***	-0.057***	-0.053***
	(0.016)	(0.015)	(0.017)
$z_{i,t-1}$	-0.099**	-0.092**	-0.083**
	(0.045)	(0.042)	(0.04)
$\Delta \log P_{i,t-1}$	0.228*		
	(0.124)		
$\Delta Cred_{i,t-1}$		0.064*	
		(0.038)	
$\Delta UR_{i,t-1}$			-0.256
			(0.264)
ξ	95.26	233.30	95.25
c	0.6323	0.6337	0.6308

Notes: P is the price level, $Cred$ is a credit measure and UR is the unemployment rate

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Model Evaluation Tests - Additional Regressors

		LMχ	P-value
(i)	Parameter Constancy	19.89	0.0303
	Remaining Heterogeneity	17.04	0.0735
(ii)	Parameter Constancy	10.75	0.3773
	Remaining Heterogeneity	10.65	0.3855
(iii)	Parameter Constancy	7.156	0.7107
	Remaining Heterogeneity	12.91	0.2286

Notes: Models (i), (ii) and (iii) are the same as in tables C.3 and C.4.

C.2.1 Long Run Alternatives

Table C.6: Panel Cointegration Test Results - Alternative Long Run

	CIPS	p-value	CIPS - trend	p-value	Westerlund	p-value
(a)	-1.91	<0.01	-2.992	0.025	2.227	0.013
(b)	-1.638	0.038	-1.513	>0.1	1.451	0.073
(c)	-1.538	0.068	-1.457	>0.1	-0.891	0.187

Table C.7: Long Run Regression Results - Alternative

	$\log W_{i,t}$	$r_{i,t}$	$\log Y_{i,t}$
(a) Coefficient	0.222**		
	(0.086)		
(b) Coefficient		-0.162	0.857***
		(0.193)	(0.063)
(c) Coefficient			0.868***
			(0.055)
R^2 (a)		0.248	
R^2 (b)		0.886	
R^2 (c)		0.885	

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: ECM Regression Results - Alternative Long Run

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z^a_{i,t-1}$	$z^b_{i,t-1}$	$z^c_{i,t-1}$
Coefficient (a)	0.213***	-0.488***	0.068***	-0.085***		
	(0.042)	(0.109)	(0.009)	(0.029)		
Coefficient (b)	0.203***	-0.544***	0.085***		-0.105*	
	(0.028)	(0.078)	(0.011)		(0.062)	
Coefficient (c)	0.205***	-0.552***	0.085***			-0.097
	(0.028)	(0.079)	(0.011)			(0.06)
R^2 (a)			0.42512			
R^2 (b)			0.38667			
R^2 (c)			0.38495			

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Linearity and Location Selection Tests - Alternative (a)

Linearity Tests		
m	LM_χ	p-value
1	12.33	0.015
2	15.46	0.051
3	20.15	0.064
Homogeneity Tests		
m	LM_χ	p-value
1	12.33	0.015
2	3.891	0.421
3	10.99	0.027

Table C.10: Linearity and Location Selection Tests - Alternative (b)

Linearity Tests		
m	LM_{χ}	p-value
1	10.93	0.027
2	15.84	0.045
3	19.42	0.079
Homogeneity Tests		
m	LM_{χ}	p-value
1	10.93	0.027
2	1.782	0.776
3	9.847	0.043

Table C.11: Linearity and Location Selection Tests - Alternative (c)

Linearity Tests		
m	LM_{χ}	p-value
1	10.78	0.029
2	15.60	0.049
3	19.24	0.083
Homogeneity Tests		
m	LM_{χ}	p-value
1	10.78	0.029
2	2.107	0.716
3	10.08	0.039

Table C.12: Smooth Transition Panel ECM Regression Results - Alternative (a)

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z^a_{i,t-1}$
Base Regime	0.229***	-0.535***	0.086***	-0.071**
	(0.048)	(0.119)	(0.013)	(0.029)
Nonlinear Part	-0.185**	0.464**	-0.064***	-0.113***
	(0.083)	(0.192)	(0.017)	(0.04)
ξ	226.0			
c	0.638			

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.13: Smooth Transition Panel ECM Regression Results - Alternative (b)

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z^b_{i,t-1}$
Base Regime	0.225***	-0.59***	0.103***	-0.078
	(0.032)	(0.083)	(0.017)	(0.067)
Nonlinear Part	-0.24***	0.495***	-0.055***	-0.129
	(0.076)	(0.156)	(0.019)	(0.086)
ξ		702.0		
c		0.626		

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Smooth Transition Panel ECM Regression Results - Alternative (c)

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z^c_{i,t-1}$
Base Regime	0.229***	-0.596***	0.104***	-0.073
	(0.033)	(0.084)	(0.017)	(0.067)
Nonlinear Part	-0.245***	0.504***	-0.055***	-0.111
	(0.08)	(0.166)	(0.021)	(0.092)
ξ		95.14		
c		0.622		

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.15: Model Evaluation Tests - Alternative Long Run

		LMχ	P-value
(a)	Parameter Constancy	7.198	0.5154
	Remaining Heterogeneity	12.96	0.1132
(b)	Parameter Constancy	12.5	0.1303
	Remaining Heterogeneity	10.74	0.2169
(c)	Parameter Constancy	12.57	0.1277
	Remaining Heterogeneity	13.3	0.1018

C.2.2 Financial Development Subindices

Table C.16: Linearity Tests - Financial Institution Development as Transition Variable

LM_χ	p-value
13.43	0.009

Table C.17: Smooth Transition Panel ECM Regression Results - Financial Institution Development as Transition Variable

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z_{i,t-1}$
Base Regime	0.226***	-0.47***	0.077***	-0.091***
	(0.044)	(0.128)	(0.012)	(0.032)
Nonlinear Part	-0.156**	0.621***	-0.048***	-0.086*
	(0.077)	(0.216)	(0.016)	(0.044)
ξ		703.7		
c		0.668		

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.18: Model Evaluation Tests - Financial Institution Development as Transition Variable

	LMχ	P-value
Parameter Constancy	5.944	0.654
Remaining Heterogeneity	11.2	0.1904

Table C.19: Linearity Tests - Financial Market Development as Transition Variable

LM_χ	p-value
8.176	0.085

Table C.20: Smooth Transition Panel ECM Regression Results - Financial Market Development as Transition Variable

	$\Delta \log Y_{i,t-1}$	$\Delta r_{i,t-1}$	$\Delta \log W_{i,t-1}$	$z_{i,t-1}$
Base Regime	0.202***	-0.425***	0.068***	-0.106***
	(0.044)	(0.127)	(0.011)	(0.033)
Nonlinear Part	-0.081	0.464*	-0.03*	-0.043
	(0.078)	(0.248)	(0.017)	(0.052)
ξ		95.24		
c		0.632		

robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.21: Model Evaluation Tests - Financial Market Development as Transition Variable

	LMχ	P-value
Parameter Constancy	6.695	0.57
Remaining Heterogeneity	13.09	0.109

Appendix D

Nonparametric Analysis of Financial Development and Consumption

D.1 Partial Regression Plots - LLLS

Figure D.1: Partial Regression Plot, Financial Development on Consumption, country fixed effects LLLS

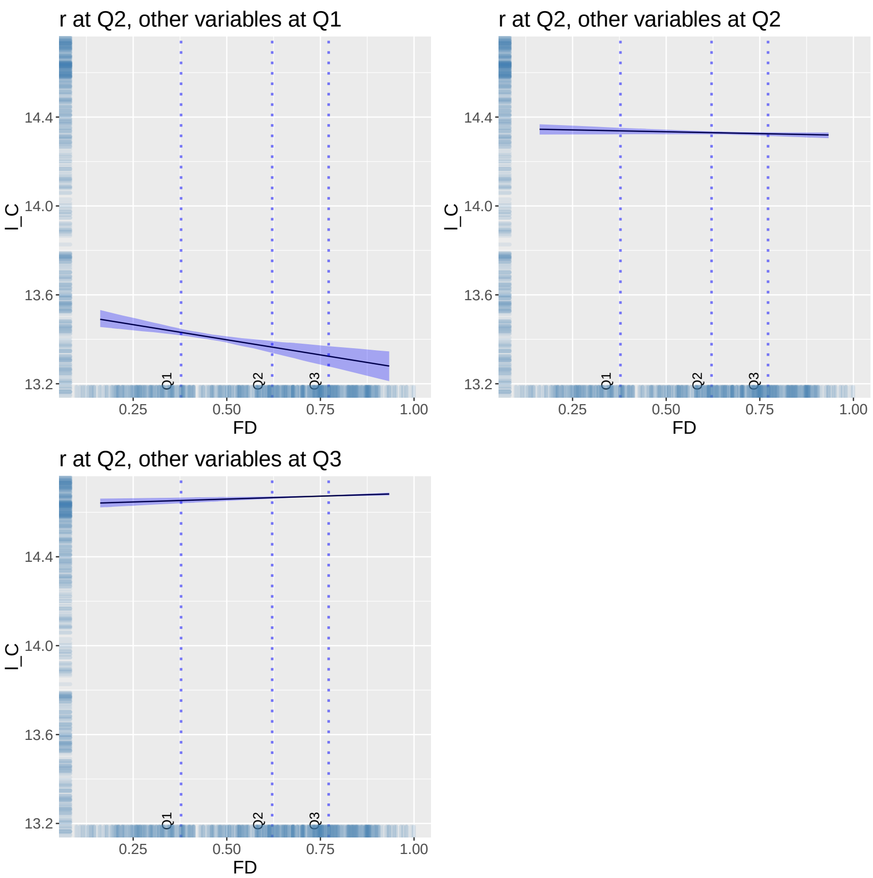


Figure D.2: Partial Regression Plot, Lagged Consumption on Consumption, country fixed effects LLLS

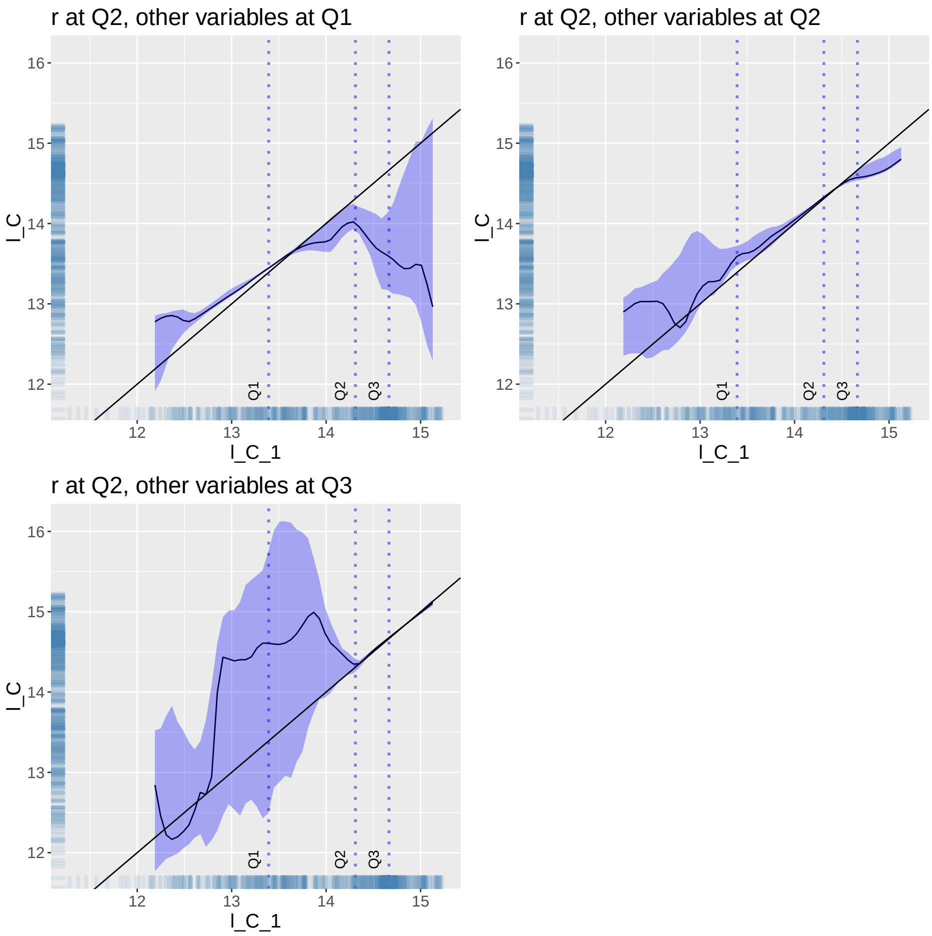


Figure D.3: Partial Regression Plot, Income on Consumption, country fixed effects LLLS

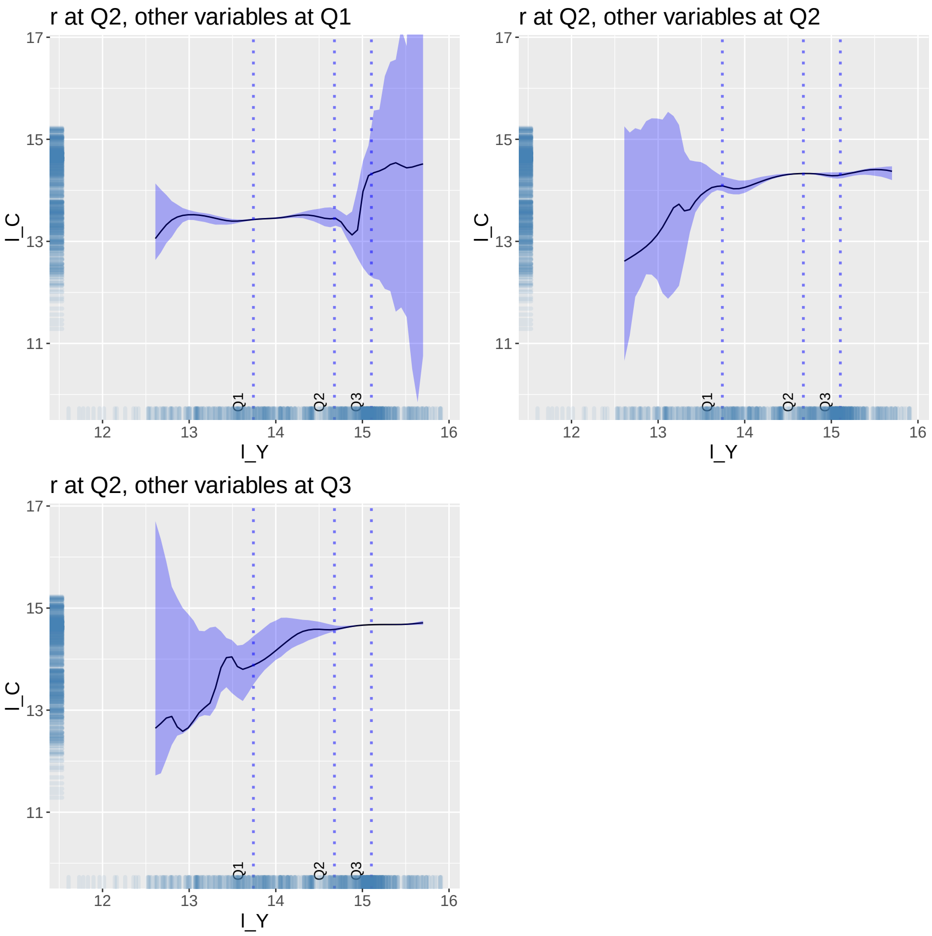


Figure D.4: Partial Regression Plot, Interest rate on Consumption, country fixed effects LLLS

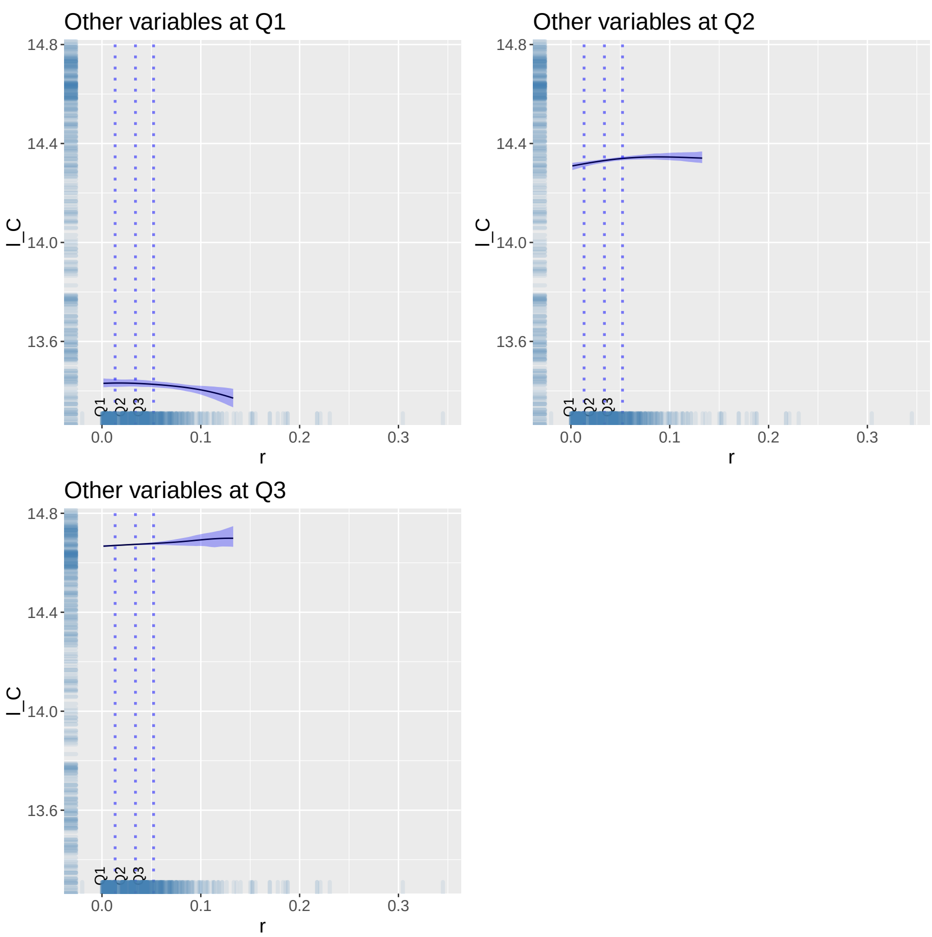
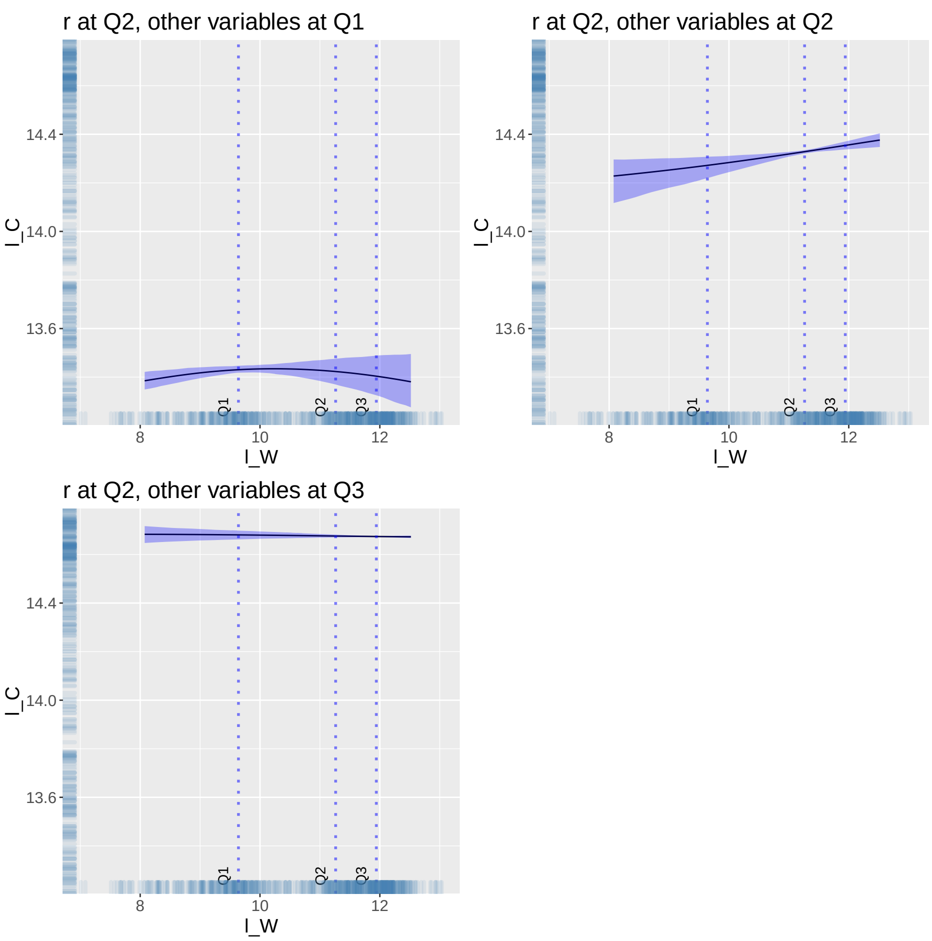


Figure D.5: Partial Regression Plot, Wealth on Consumption, country fixed effects LLLS



D.2 Gradient Plots - LLLS

Figure D.6: Gradient Plot, Financial Development on Consumption, country fixed effects LLLS

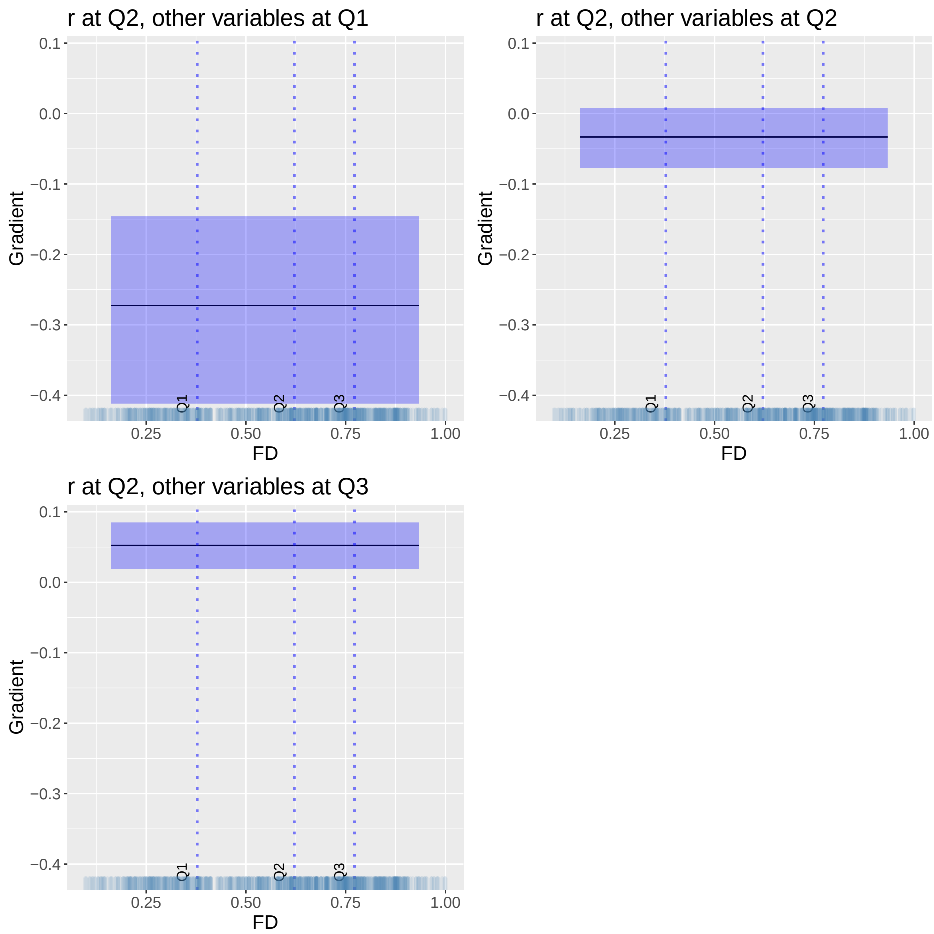


Figure D.7: Gradient Plot, Lagged Consumption on Consumption, country fixed effects LLLS

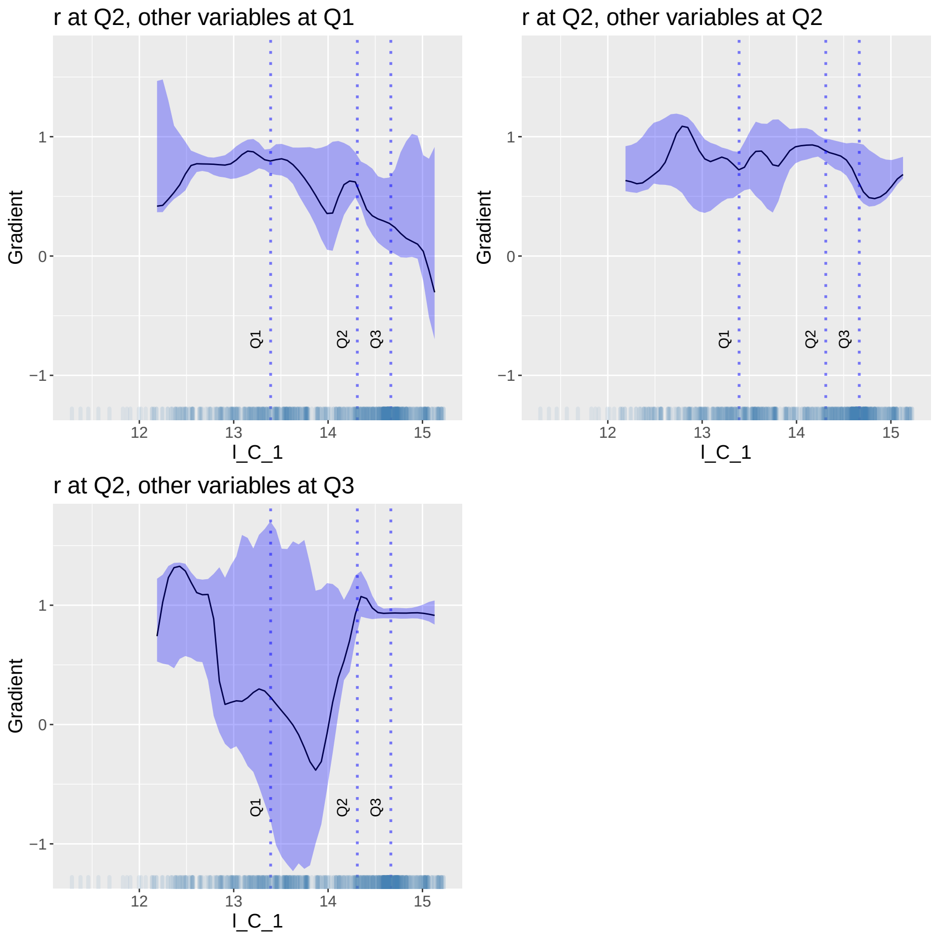


Figure D.8: Gradient Plot, Income on Consumption, country fixed effects LLLS

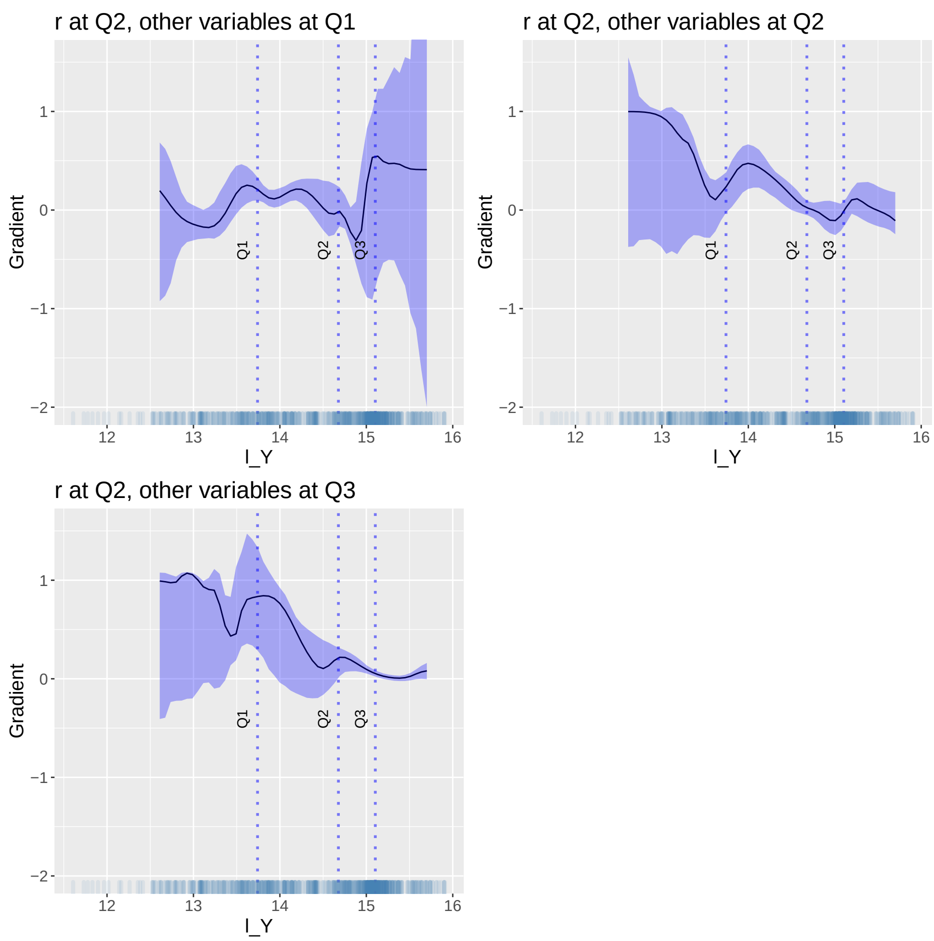


Figure D.9: Gradient Plot, Interest rate on Consumption, country fixed effects LLLS

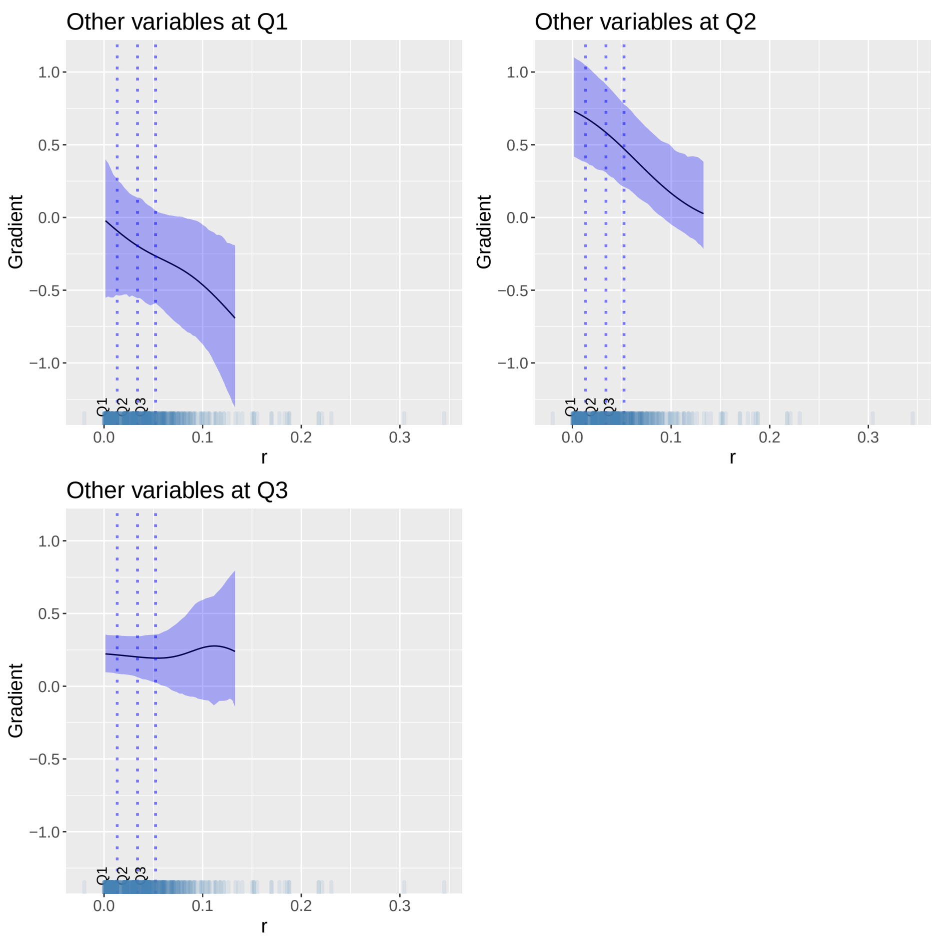
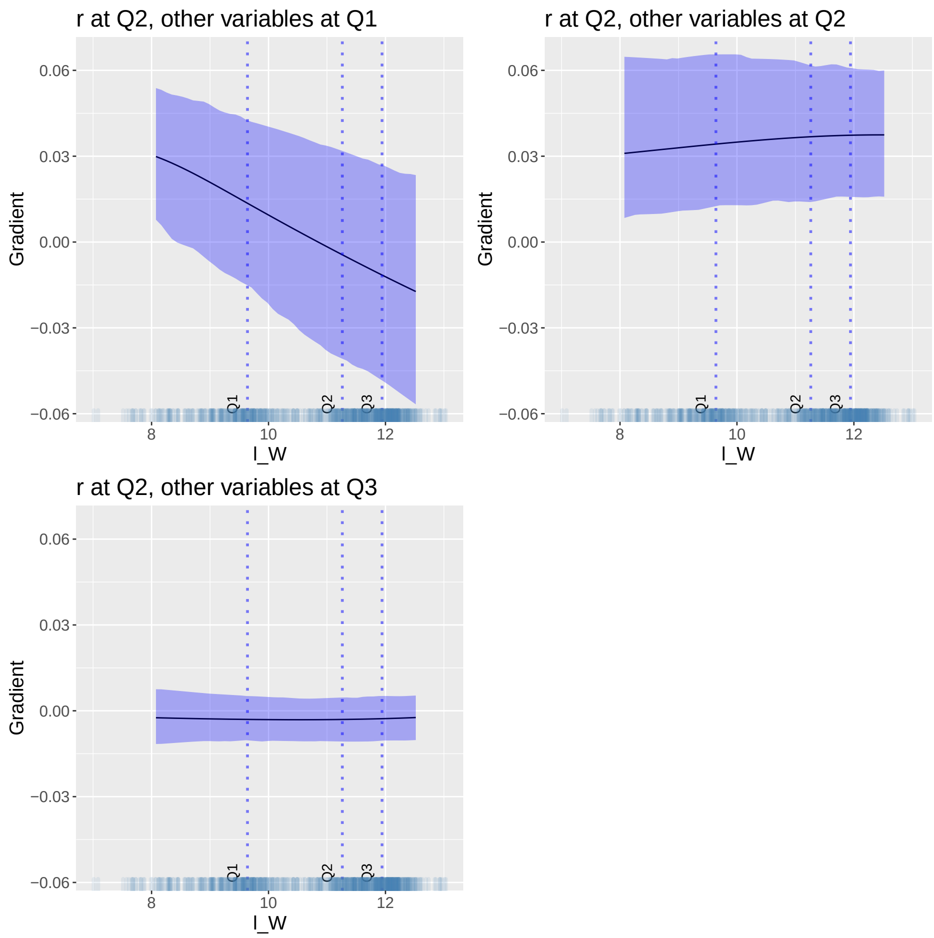


Figure D.10: Gradient Plot, Wealth on Consumption, country fixed effects LLLS



D.3 Partial Regression Plots, by Financial Development Levels

Figure D.11: Partial Regression Plot for different values of FD, Lagged Consumption, country fixed effects LLLS

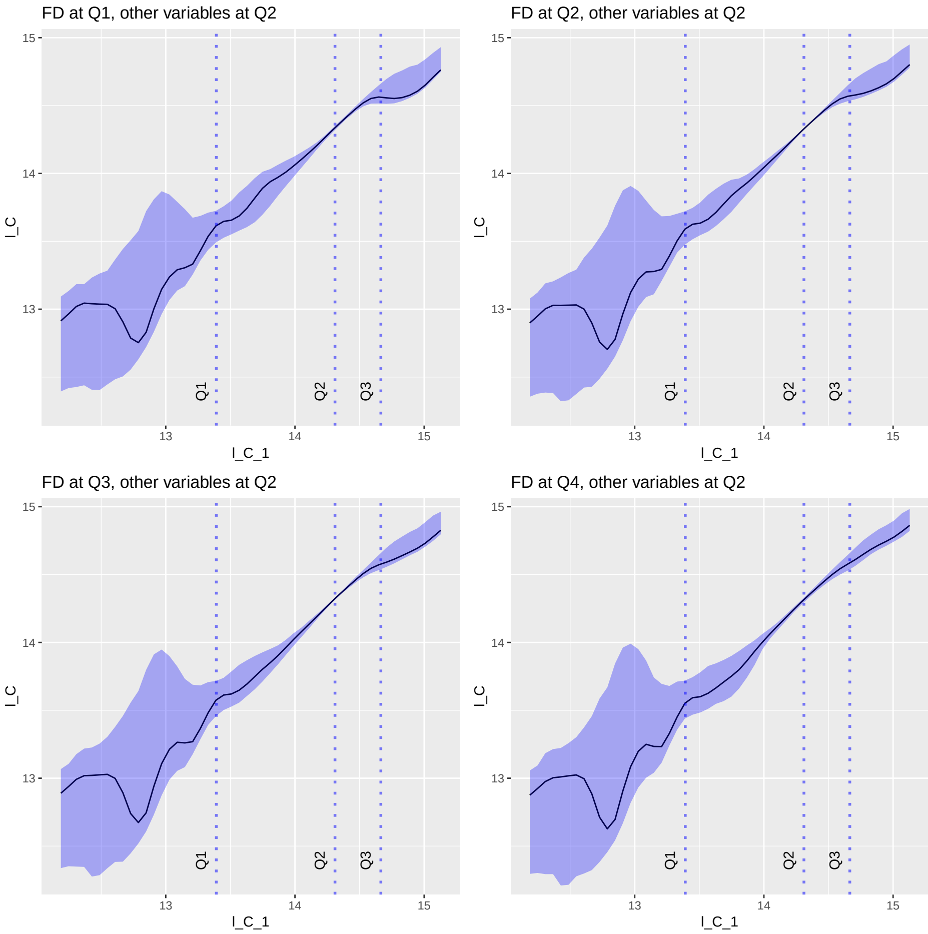


Figure D.12: Partial Regression Plot for different values of FD, Income, country fixed effects LLLS

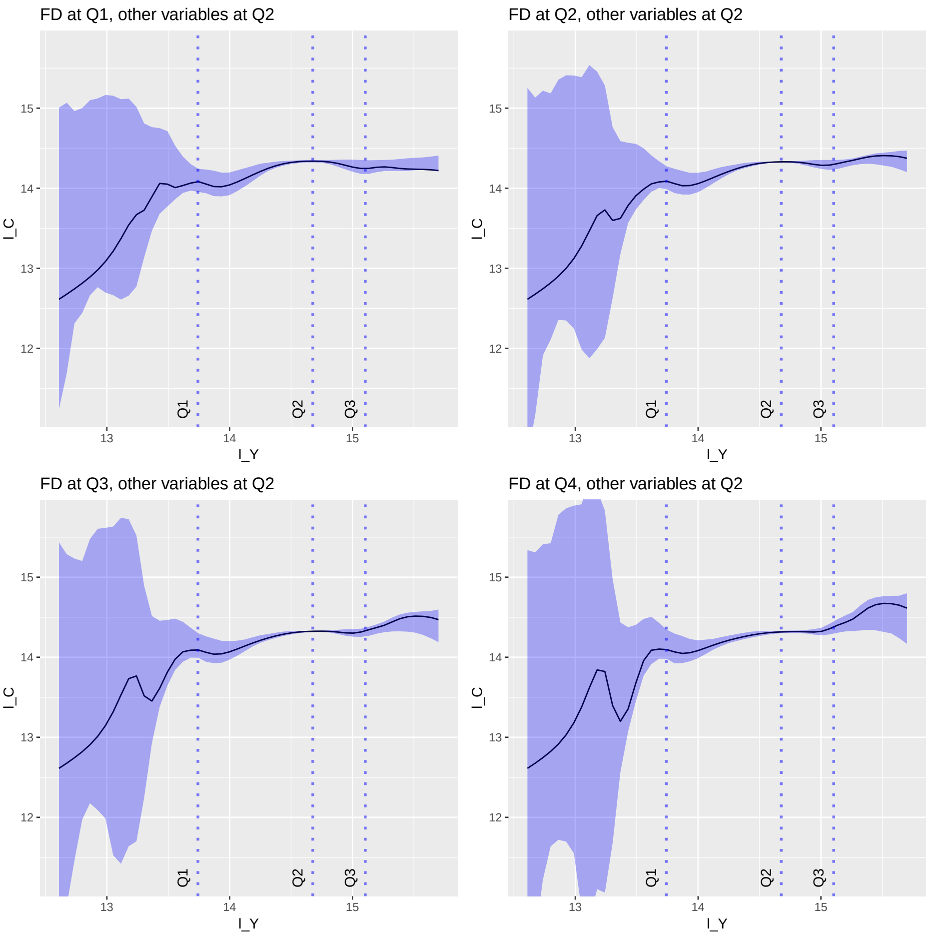


Figure D.13: Partial Regression Plot for different values of FD, Interest rate, country fixed effects LLLS

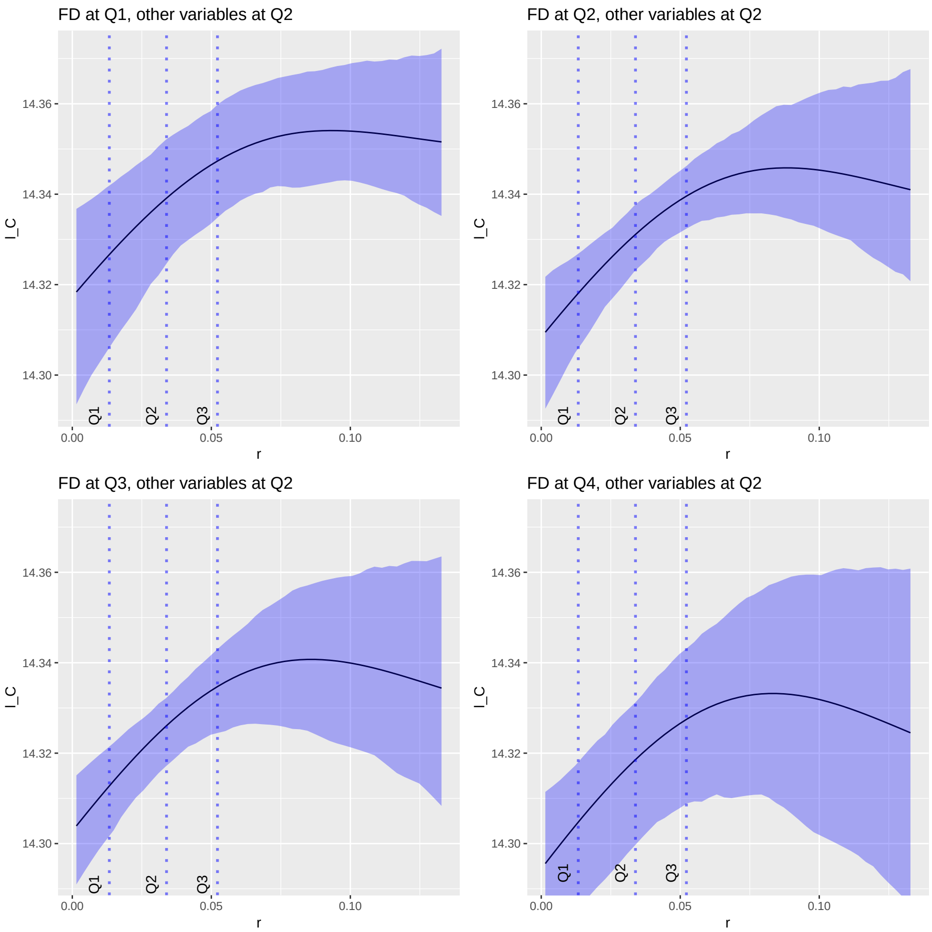


Figure D.14: Partial Regression Plot for different values of FD, Wealth, country fixed effects LLLS