Master thesis

Fiscal Multipliers in Italy

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Abstract

I estimate the fiscal multiplier in Italy at the provincial level. Following Sarto (2018), I relax the assumption of the homogenous response of output growth to aggregate shocks across provinces. For this purpose, I use grouped fixed effects estimator developed by Bonhomme and Manresa (2018) and discuss the conditions needed for its consistency in endogenous regressors case. I find the estimate of the provincial multiplier of approximately 1. Then, I apply a theoretical framework suggested by Nakamura and Steinsson (2014) to relate this multiplier to the aggregate multiplier and find that the latter may be much higher than 1 in the absence of responsive monetary policy.

Introduction

What is the effect of government spending shock on output? The estimation of the fiscal multiplier - the percentage increase in output resulting from the increase in government spending by 1 percent of GDP - is a common approach to study the transmission of fiscal policy.

I consider two types of fiscal multipliers: relative and aggregate multipliers[1]. The relative multiplier is the result of a cross-sectional analysis of fiscal policy within a country, and it reflects how output growth responds to the increase in government spending relative to the average region. Given the process of spending, it depends only on economy fundamentals and on the way spending is financed since it is computed keeping aggregate policy constant across regions. The aggregate multiplier, in contrast, measures the response of the whole national economy to total government spending, and it may depend substantially on the aggregate path of monetary and budget policies.

The estimation of relative multipliers is becoming a wide—spread approach in the empirical literature on fiscal stimulus. This trend is motivated by the identification advantages that panel data methods bring to the table: they allow to make use of the spacial variation in spending and to keep aggregate policies and business cycle movements fixed. One of the challenges connected with this strategy, however, is that regions usually differ in many dimensions (e.g. structure of production, level of employment, institutions, preferences). These differences imply heterogenous response to aggregate shocks (Sarto (2018)), which cannot be fully captured by the inclusion of standard time effects.

The common ways of controlling for differences across units, such as the inclusion of region-specific dummies, or the use of weights in the regression, do not help to account for time-varying unobserved heterogeneity either, and the only case when the fixed effects model produces consistent estimates of the relative multiplier is when the heterogeneity is

[1] I follow the terminology from Nakamura and Steinsson (2014)

unrelated to the source of exogenous variation in government spending usually measured by instruments.

In this project, I measure the relative multiplier in Italy using grouped fixed effects model developed by Bonhomme and Manresa (2018). This estimator assumes different time profiles of the geographical units assigned to different groups, and thus allows me to effectively control for the heterogenous response of output growth to aggregate shocks across Italian provinces.

To address the endogeneity concerns, I incorporate grouped fixed effects approach to the instrumental variable framework suggested by Acconcia et al. (2014). The authors found a convenient setting to analyze multipliers in the cross-section. At the beginning of the 1990-s in Italy, the central governments were given the power to remove city councils for the reasons related to mafia infiltration. They were replaced with external authorities, and some projects related to public works were frozen while the investigation was carried out. This resulted in an immediate drop in government spending that, given investigation activity across provinces, was not likely to be related to their economic activity. Notice, however, that the dismissals could have been correlated with aggregate shocks, or with the provinces fundamentals which determine the response of their output growth to these shocks, and the inclusion of grouped fixed effects allows me to control for these correlations.

I estimate relative multiplier to be close to 1. It means that a decrease in relative per capita government purchases in one province by 1 percent of province value added leads to the decrease in relative per capita value added by approximately 1 percent. I calibrate the model of monetary union suggested by Nakamura and Steinsson (2014) to relate this multiplier to the aggregate multiplier in Italy. I find that the estimated relative multiplier lines up well with the relative multiplier reproduced by the New Keynesian model. This model predicts the aggregate multiplier to be higher than 1 under the accommodative monetary policy, such as a fixed nominal rate regime. It can be explained by the absence of a "crowding-out" effect on private consumption in response to the government spending shock.

This work uses data and identifying assumptions needed for instrumental variables method from Acconcia et al. (2014), where the authors estimated the relative fiscal multiplier for Italy with a standard fixed effects approach. I relax the assumption about the homogenous response of provinces to aggregate shocks and allow different groups of provinces to have different time effects. This grouped fixed effects approach was developed by Bonhomme and Manresa (2018). While the authors consider the case with exogenous regressors, I discuss under which assumptions grouped fixed effect estimator is consistent in the endogenous framework.

Sarto (2018) was the first to account for the heterogenous response of regions to aggregate shocks in the analysis of fiscal multipliers. The author approximates aggregate shocks by factors retrieved from interactive-effects model and computes the elasticities of output growth to total spending growth for each state in the US. This allows the author to estimate the aggregate multiplier directly from data. Since the small number of time periods and the lack of the variation in council dismissals across provinces do not allow me to retrieve factors and to consider separate regressions for each province, I use grouped fixed effects approach to estimate relative multipliers and then compute the aggregate multiplier imposing structural restrictions from the theoretical model.

A model of monetary union that I consider is based on Nakamura and Steinsson (2014). The authors suggest a framework to interpret the relative fiscal multiplier estimated from subnational level data, and to relate the multiplier to the aggregate response of the economy to the government spending shock. Farhi and Werning (2016) and Chodorow-Reich et al. (2012) also discuss the theoretical connection between relative and aggregate multipliers.

Overall, this work is heavily related to the literature on the cross-sectional estimation of fiscal multipliers (Fishback and Kachanovskaya (2010), Clemens and Miran (2012), Porecelli and Trezzi (2014), Shoag (2015)), on interactive-effects model with homogenous coefficients developed by Bai (2009), and on theoretical models of monetary union (Benigno and Benigno (2003), Gali and Monacelli (2008)).

The remainder of the paper proceeds as follows. Section I explains why standard fixed effects models may produce biased estimates of the relative multipliers if one assumes provinces to be heterogenous. Section II suggests a methodology to estimate the relative multiplier in Italy and presents the results from the Monte Carlo experiment. Section III presents the results from the baseline estimation, compares them with Acconcia et al. (2014) and checks their robustness. Section IV describes the calibration of the model and summarizes the results. Section V concludes.

I How to control for heterogeneity across provinces?

Let us start with the assumption that provinces in Italy are heterogenous in their response of output growth to the policies at the national level. Theoretically, Sarto (2018) rationalizes it with different production functions that imply different responses to aggregate shocks. Moreover, economic agents located in different geographical units may get different signals about the state of the national economy, which also explains their different actions at each point in time. Empirically, heterogeneity comes from a wide range of sources including the structure of production, the quality of institutions, cultural and historical differences.

Then the natural way to think about the process of output growth would be (1) (Bai, 2009):

$$Y_{it} = \beta X_{it} + \lambda_i F_t + u_{it} \tag{1}$$

where Y_{it} - output growth in province i at time t; λ_i are the loadings representing different elasticities to aggregate shocks; F_t are the factors, proxies for aggregate shocks, X_{it} - variables of interest; u_{it} - random error.

Suppose the model (1) is estimated with a standard fixed effects approach[2]. All the variables are transformed to the deviations from the provinces-specific means:

$$Y_{it} - \bar{Y}_i = \beta(X_{it} - \bar{X}_i) + \lambda_i(F_t - \bar{F}) + u_{it} - \bar{u}_i \tag{2}$$

Since $F_t \neq \bar{F}$, within transformation does not help to get rid of unobserved heterogeneity. This implies that β is consistently estimated only if $E[X_{it}F_t] = 0$, or, in other words, if variables of interest are not correlated with aggregate shocks. One of the ways to relax the assumption of zero correlation between regressors and factors would be to estimate the

[2]For simplicity, I assume that only provinces fixed effects are included in the regression, but the same analysis can be done for the inclusion of time effects

panel data interactive effects model developed by Bai, 2009. The author suggests an iterative algorithm, which on the first stage defines factors using the method of principal components and then retrieves the coefficients of interest controlling for these factors in panel data regression.

When the number of periods is small, however, a researcher is not able to define factors consistently. In this case, grouped fixed effects estimator developed by Bonhomme and Manresa, 2018 may be applied. It allows for grouped patterns of heterogeneity across units in question:

$$Y_{it} = \beta X_{it} + \alpha_{g_i t} + u_{it} \tag{3}$$

where $g_i \in [1, ..., G]$ are group membership variables, which share the same time profile α_{gt}. This model is a particular case of (1), where λ_i and F_t are $(G \times 1)$ vectors, and $\lambda_{ig} = 1\{g_i = g\}$ and $F_{tg} = \alpha_{gt}$.

To estimate a model (3) one can apply an iterative algorithm, where each iteration proceeds in two steps. The first step defines group membership, so as to minimize the distance between the outcome variable net of the effect of covariates and the time effects. In other words, provinces with similar time profiles are grouped together. The second step delivers the estimates of the coefficients controlling for grouped time effects.

Bonhomme and Manresa, 2018 show that the algorithm described above yields to the consistent estimates of β under the assumption that X_{it} includes exogenous and predetermined regressors. To account for endogeneity, however, I need to modify the estimation procedure, and in the next section, I discuss a possible way to address this problem.

II Grouped fixed effects with endogenous regressors

This section motivates and describes the estimation procedure applied to estimate the relative fiscal multiplier in Italy. First, I describe the data generating process, next I move to the estimation algorithm, and, finally, present the results from the Monte Carlo experiment.

II.A Data generating process

The main endogeneity concern in fiscal stimulus framework comes from the fact that government spending directly responds to output growth in the same period. This implies the simultaneous relationship between government spending and output, and one of the ways to summarize it is to consider the system of equations:

$$Y_{it} = \beta_G G_{it} + \beta_X X_{it} + \alpha_{g_i t} + w_{it}^Y \tag{4}$$

$$G_{it} = \theta_Z Z_{it} + \kappa_Y Y_{it} + \theta_X X_{it} + w_{it}^G \tag{5}$$

$$Z_{it} = \delta \alpha_{g_i t} + \delta_X X_{it} + w_{it}^Z \tag{6}$$

where Y_{it} is output growth, G_{it} is government spending growth, $\alpha_{g_i t}$ are grouped time effects, Z_{it} is the instrument, and X_{it} are the control regressors that may include predetermined variables.

In the equation (5) I argue that the heterogeneity in the response of government spending to aggregate shocks is mainly driven by the heterogeneity in the response of output growth to these shocks. Government authorities first consider the level of economic activity within a province when they make their investment decisions. Since the economic activity responses to aggregate shocks are different across groups of provinces (equation (4)), government spending response to aggregate shocks will change as well across these groups.

I allow the instrument and other control variables to be correlated with $\alpha_{g_i t}$. I also assume that $\alpha_{g_i t} \perp w^G_{it} \perp w^Y_{it} \perp w^Z_{it}$.

II.B Estimation procedure

First, I rewrite the equations (4) and (5) in reduced form (express all endogenous variables with exogenous ones):

$$\begin{pmatrix} Y_{it} \\ G_{it} \end{pmatrix} = \frac{1}{1-\beta_G k_Y}\left[\begin{pmatrix} \beta_G \theta_Z \\ \theta_Z \end{pmatrix} Z_{it} + \begin{pmatrix} \beta_G \theta_X + \beta_X \\ k_Y \beta_X + \theta_X \end{pmatrix} X_{it} + \begin{pmatrix} 1 \\ k_{g_i Y} \end{pmatrix} \alpha_{g_i t}\right] + \begin{pmatrix} u^Y_{it} \\ u^G_{it} \end{pmatrix} \tag{7}$$

where $u^Y_{it} = \frac{w^Y_{it} + \beta_G w^G_{it}}{1-\beta_G k_Y}$ and $u^G_{it} = \frac{k_Y w^Y_{it} + w^G_{it}}{1-\beta_G k_Y}$. Notice, that I allow the response of government spending to aggregate shocks ($k_{g_i Y}$) to be different for different groups.

To get a consistent estimator of β_G I suggest the following estimation procedure. First, the group assignment is defined from the reduced form equation for Y_{it} (equation (7)) with the same algorithm as in Bonhomme and Manresa, 2018. In other words, to retrieve the group membership I minimize the following objective:

$$(\hat{g}_i, \hat{\theta}, \hat{\gamma}) = \arg\min_{g_i, \theta, \gamma} \sum_t \sum_i (Y_{it} - \theta Z_{it} - \gamma X_{it} - \alpha_{g_i t})^2 \tag{8}$$

Once the group membership is known, I estimate β_G with 2-SLS regression contrilling for grouped time effects on each step. In particular, the first step extracts the exogenous variation in government spending:

$$\hat{G}_{it} = \hat{\theta} Z_{it} + \hat{\gamma} X_{it} + \hat{\alpha}_{\hat{g}_i t} \tag{9}$$

The second step uses this variation in the regresison for output growth:

$$(\hat{\beta}, \hat{\alpha}_{g_i t}) = \arg\min_{\beta, \alpha} \sum_t \sum_i (Y_{it} - \beta_G \hat{G}_{it} - \beta_X X_{it} - \alpha_{\hat{g}_i t})^2 \tag{10}$$

The algorithm described above delivers a consistent estimator of β_G for a given number of groups. Since in reality a researcher does not know the true number of groups, I perform the estimation for all numbers of groups in the range $2-12$ and choose the optimal number of groups using Bayesian Information Criteria (BIC). It is usually applied to estimate the optimal number of factors in interactive-effects models, and it is shown to perform well for grouped fixed effects case (Bonhomme and Manresa, 2018). I compute BIC from the reduced form regression that I use to define groups:

$$BIC(G) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \hat{\theta}Z_{it} - \hat{\gamma}X_{it} - \hat{\alpha}_{g_i t})^2 + \hat{\sigma}^2\frac{GT+N+K}{NT}\ln NT \tag{11}$$

where G is the number of groups and $\hat{\sigma}^2 = \frac{1}{NT-GT-N-K}\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \hat{\theta}Z_{it} - \hat{\gamma}X_{it} - \hat{\alpha}_{g_i t})^2$ for the maximum number of groups. The optimal number of groups minimizes BIC.

The consistency of the estimator of β_G that I get on the last stage follows from the consistency of grouped fixed effects estimator, and from the consistency of the instumental variables estimator. Since I do not prove it formally in this work, I perform Monte Carlo simulations to confirm the convergence of the estimator to the true parameter value.

II.C Monte Carlo experiment

I perform two Monte Carlo simulations to evaluate the performance of the estimator described in the previous section.

In the first experiment, I look at the behavior of the estimator when both dimensions of panel diverge ($N, T \to \infty$). I simulate the data from the reduced form regression (7) with one instrumental variable Z_{it} and one control variable $X_{it} = G_{it-1}$. I pick the values of the true parameters (β_G, β_X) to express the reduced form coefficients. In this experiment, I generate the regressors and group specific means as random vectors, allowing for the correlation between the instrument and grouped time effects as in (6). Also, I assume that group membership is consistently defined so that the estimation of the simulated data proceeds with the true group assignment. In the second experiment, I consider the misclassification probability.

Table 1 presents the results of the estimation for a different number of groups and compares it with the performance of standard fixed effects estimator. We can see that when both dimensions of panel tend to infinity the grouped fixed effects estimator converges to the value of a true parameter. It outperforms a standard fixed effect estimator, which bias increases with a number of groups.

Table 1: Bias of Grouped Fixed Effects Estimator

	β_G (G_{it})			β_X (G_{it-1})		
	True	GFE	FE	True	GFE	FE
$G = 2$	1.5	1.4999	1.4696	0.5	0.5001	0.4919
$G = 5$	1.5	1.5001	1.4531	0.5	0.5000	0.4922
$G = 10$	1.5	1.5000	1.4472	0.5	0.5000	0.4902

Note: Table shows the mean of the grouped fixed effects estimates and standard fixed effect estimates of equation (10) across 500 Monte Carlo simulations for $N = 300$, $T = 300$.

The purpose of the second experiment is to evaluate the performance of the grouped fixed effects estimator when the number of time periods is small. I set the dimensions of the panel to be the same as in my empirical dataset $N = 94$, $T = 10$. I use the same vectors of instruments that I have in the data. I set the true parameters of β_G, β_X, and $\alpha_{g_i t}$ equal to the ones estimated on the real dataset for a given number of groups. Finally, I generate w_{it}^Y and w_{it}^G as iid Normal variables with the variances

$$\begin{pmatrix} \sigma_{wy}^2 \\ \sigma_{wg}^2 \end{pmatrix} = (1 - \beta_G k_Y)^2 \begin{pmatrix} 1 & \hat{\beta}_G^2 \\ k_Y^2 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{uy}^2 \\ \sigma_{ug}^2 \end{pmatrix} \tag{12}$$

where σ_{uy}^2 and σ_{ug}^2 are the means of squared residuals of equations (10) and (9) accordingly.

The correlation between the simulated and the true data is on average 0.6 for output growth and 0.2 for government spending growth.

Table 2: Bias of Grouped Fixed Effects Estimator

	β_G (G_{it})			β_X (G_{it-1})			Misclassified
	True	GFE	FE	True	GFE	FE	
$G = 2$	1.169	1.182	1.123	0.512	0.522	0.469	4.12 %
$G = 3$	1.068	1.063	1.039	0.510	0.509	0.492	5.22 %
$G = 4$	0.60	0.694	0.953	0.352	0.397	0.489	8.18 %
$G = 5$	0.941	0.959	1.013	0.474	0.483	0.486	8.38 %

Note: Table shows the mean of the grouped fixed effects estimates and standard fixed effect estimates of equation (10) across 500 Monte Carlo simulations for $N = 94$, $T = 10$.

Following Bonhomme and Manresa, 2018, I also compute misclassification probability for each number of groups that I consider. Table 2 presents the results of the estimation for the number of groups from 2 to 5. While the point estimates produced by the grouped fixed effects approach are consistently close to the true parameters' values, the bias of standard fixed effects estimates varies across the number of groups and may exceed 50% of the paramter value ($G = 4$). Although the misclassification probability is reasonably small (less that 10%), it increases with the number of groups.

III Relative multiplier: data and estimation results

In this section, I describe the dataset I use for estimation of the relative multiplier and present the estimation results.

III.A Data

I consider the same dataset as in Acconcia et al., 2014. It includes 94 provinces[3] and 10 time periods from 1990 to 1999. The outcome variable (Y_{it}) is a real per capita year-on-year growth of value added, and the variable of interest (G_{it}) is a real per capita year-on-year change in public investment in infrastructure as a share of value added. The public investment includes spending on transport, sanitation, reclamation, energy, and buildings. The authors used the data from ISTAT Annual Reports to construct these variables.

Two instruments are considered to account for the relative population in the city and for the timing of council dismissals withing a year and include

1. A number of municipalities put under compulsory administration provided that the official decree is published in the first semester of the year, weighted by the share of the province population living in these municipalities;

2. A number of municipalities put under compulsory administration provided that the average number of days between the dismissal of the city council and the year end is less than 180, weighted by the share of the province population living in these municipalities.

Following Acconcia et al. (2014), I consider two groups of control variables. The aim of the first group is to account for the other possible channels through which mafia infiltration can affect the local businness cycle. These controls include the first difference of the number of people reported for the mafia-type association, extortion, mafia-related murders, corruption.

[3] I drop the province Trieste from the original dataset because of the high volatility in output growth

These variables represent the result of the investigation in a given province and are the proxies for the scale of mafia activities. The second set of variables controls for local business cycle conditions and include up to two lags of the growth in per capita employment.

III.B Estimation Results

Table 3 reports the results of grouped fixed effects estimation and compares them with the ones obtained in Acconcia et al., 2014. First, let me notice the role of population weights in the analysis of fiscal multiplier. The baseline specification in Acconcia et al., 2014 weights each observation by the relative population in a province, and this strategy increases the point estimates of the multiplier. As I see it, the main reason for using weights, in this case, is to make the multiplier more representative in terms of the response of the national economy. Another motivation is to account for heterogeneity across different provinces. In this work, I have chosen another way of the aggregate multiplier estimation, which incorporates the aggregate path of policies. Also, the grouped fixed effects estimator already controls for the heterogeneity across provinces, so that the use of population weights is redundant in this work.

The forth column of the Table 3 presents the contemporaneous multiplier of 0.99 when the number of groups is 6, and I consider this specification to be the baseline one since this number of groups consistently minimizes BIC[4]. Overall, the grouped fixed effects point estimates are lower than the ones obtained with a standard fixed effects model (1.55), and this result holds for the number of groups from 4 to 10[5]. This implies that the part of the output response to aggregate shocks of some groups of provinces is falsly attributed to the change in government spending when additive fixed effects model is considered.

The difference, however, is not statistically significant, and none of the multipliers is

[4] I consider different alternatives for the maximum number of groups from 10 to 12

[5] Table 7 in the Appendix

significantly higher than 1. It can be explained by the low variation in the instrument[6], which can be the reason for the moderate correlation between the instruments and the grouped time effects. Although the correlation is not high enough to make the results statistically different, it is not equal to zero, which is justified by the increase in the first stage F-statistic once I control for the heterogenous response to time effects. I also estimate the correlation between grouped averages of the first instrument with grouped time effects estimated from the equation (10) to be -0.19 (-0.17 for the second instrument).

Table 3: Public Spending Multiplier

	Acconcia et al. (2014)			Grouped Fixed Effects
	OLS	IV	IV	IV
G(t)	0.23^{**}	1.55^{***}	1.27^{**}	0.99^{*}
	[0.07]	[0.43]	[0.43]	[0.47]
G(t-1)	0.26^{**}	0.79^{***}	0.62^{**}	0.45^{**}
	[0.08]	[0.19]	[0.21]	[0.19]
Y(t-1)	-0.16^{*}	-0.20^{**}	-0.13^{*}	0.06
	[0.06]	[0.06]	[0.06]	[0.06]
F-stat		11.83	7.88	13.25
Population weights	yes	yes	no	no
Observations	950	950	950	940

Note: The first column of the Table reports the results from OLS regression, while the other columns present the estimation results from the second step of IV regression. Reported in brackets are the standard errors clustered by region. The dependent variable is a year-on-year growth of value added. Control variables include the first difference of the number of people reported for mafia-related crime (up to two lags), two lags of the growth in per capita unemployment, the second and the third lags of city council dismissals. The first three regressions also control for year and province fixed effects. The last regression instead controls for the grouped fixed effects when the number of groups is 6.

Differently from Acconcia et al., 2014, I do not get the significant response to the lagged dependent variable, which implies that the dynamic multiplier is equal to 1.44, the sum of

[6] Only 18 provinces out of 94 have a non-zero number of city council dismissals

the coefficients of G_{it} and G_{it-1} (1.95 in Acconcia et al., 2014). This can be explained by the absence of a mechanical bias that takes place when fixed effects are included in a dynamic panel data model.

I also refer the reader to the Figures 1 and 2 in the Appendix. Figure 1 shows how the groups are defined. Although I impose no restrictions on the group membership, provinces that belong to the same group usually appear close to each other. The role of geographical pattern in group assignment may be explained by historical differences (for example, in southern regions, that were more subsidized by the national government, the output growth is more sensitive to the state of the national economy), or by the different structure of production and employment. Figure 2 presents time effects specific for each group when the number of groups is 4 and 6. Although the sign of the effect is usually the same across groups, the magnitude differs and the trends are not parallel, implying that the heterogeneity changes over time.

III.C Alternative specifications

To check the robustness of results, I consider several alternative specifications of the model (Table 4 provides a summary). First, I drop the controls for the scale of mafia activities to see if the police investigation affects output independently from government spending cuts. Table 8 in the Appendix presents the results. Group membership does not change in this case, and neither does the optimal number of groups. The results of the baseline specification suggest the relative multiplier of 0.89, which is only slightly lower than when I include controls (0.99). Similiraly with Acconcia et al., 2014, it provides the evidence of a positive, if any, the effect of a police investigation against the Mafia. First step F-statistic rises to 24.26 implying the presence of correlation between the instruments and mafia-related control variables.

Table 4: Public Spending Multiplier: Robustness Checks

	Drop Mafia controls	Drop North	Provinces Fixed Effects	Groups by regions
G(t)	0.89*	1.21**	0.57	1.00
	[0.37]	[0.39]	[0.43]	[0.66]
G(t-1)	0.41**	0.56***	0.35*	0.42
	[0.14]	[0.17]	[0.17]	[0.26]
Y(t-1)	0.05	-0.04	-0.09*	-0.03
	[0.05]	[0.11]	[0.04]	[0.07]
F-stat	24.26	5.32	4.36	3.50
Number of groups	6	3	5	19
Observations	940	340	940	940

Note: Each column presents the estimation results from the second step of IV regression (equation (10)). Reported in brackets are the standard errors clustered by region. Each regression controls for two lags of the growth in per capita unemployment and the second and the third lags of city council dismissal. Each regression apart from the first one also controls for the first difference of the number of people reported for mafia-related crime (up to two lags). In the second regression the sample is restricted to southern provinces. The third regression also includes provinces fixed effects. The fourth regression defines groups as Italian regions.

Next, I estimate the multiplier restricting the sample to southern provinces (Table 9). Due to the lower number of observations, the optimal number of groups in this case is 3, which implies the relative multiplier of 1.21 and the dynamic effect of 1.77. The result suggests that the output growth in southern provinces decreases more in response to the spending cuts than in the average province in Italy.

Moreover, I allow for time invariant provinces fixed effects in addition to the grouped time effects and estimate the model in deviations from the provinces specific means (Table 10). The optimal number of groups according to BIC, in this case, is 5. The point estimate of the relative multiplier drops and become insignificant, which may be explained by a large number of additional controls (94). The results, however, should be treated with caution because of the bias of the fixed effect estimator in dynaminc panels.

Finally, I skip the group assignment step and define groups as Italian regions. Interestingly, the point estimate of the relative multiplier remains unaffected and is equal to 1 (Table 4) as in the baseline model. The significance and the F-statistic drop, and it can be attributed to a large number of regressors (if the number of groups is 19, the number of grouped time controls is 190 for 10 periods). This result indicates how efficient the group assignment algorithm works. Without imposing any restrictions, it allows accounting for time-changing heterogeneity keeping the number of controls small.

IV From relative multiplier to aggregate multiplier

In this section, I describe and calibrate a model of a monetary union (Nakamura and Steinsson, 2014) to relate the multiplier I get from the empirical experiment to the aggregate multiplier. I discuss the scope for national policy to affect the multiplier in the different economic environment (price stickiness, market completeness).

In the model I consider, provinces are homogenous, which may seem to be at odds with the spirit of the empirical section. If I assume the heterogeneity across provinces, however, the model would imply different relative multipliers for each province (Sarto, 2018) that I do not estimate empirically. In this regard, the empirical experiment performed above may be considered as a partial departure from the homogeneity case.

IV.A Model of Monetary Union

The model is based on Nakamura and Steinsson, 2014, and I refer the reader to this paper for a detailed description. In this subsection, I summarize the setting and the ingredients that are key for the multiplier.

The model consists of two provinces that belong to a monetary and fiscal union. Households in each province solve the following optimization problem:

$$\max_{C_t, L_t(x), B_{t+1}(x)} E_0 \sum_{t=0}^{\infty} \beta^t u(C_t, L_t(x)),$$

s.t.:

$$P_t C_t + E_t[M_{t,t+1} B_{t+1}(x)] \leq B_t(x) + (1-\tau_t) W_t(x) L_t(x) + \int_0^1 \Pi_{ht}(z) dz - T_t$$

where β is the subjective discount factor, C_t is household consumption of a composite consumption good, $L_t(x)$ is household supply of differentiated labor input x; $B_{t+1}(x)$ is a state contingent payoff of the portfolio of the financial securities of household x; $M_{t,t+1}$ is the stochastic discount factor that prices this payoff in period t; τ_t is a labour income tax, $W_t(x)$ is the wage of the home household of type x; $\Pi_{ht}(z)$ is the profit of firm z, and T_t denotes lump sum taxes.

Households of the home province consume local goods and the goods imported from another province and are biased to home production. There is a continuum of varieties in each province, and households take the price for each variety as given. The cost minimization problem yields the following demand curve for home goods (same logic for foreign goods):

$$C_{H,t} = \phi_H C_t \left(\frac{P_{Ht}}{P_t}\right)^{-\eta}$$

$$c_{ht}(z) = C_{Ht} \left(\frac{p_{ht}(z)}{P_{Ht}}\right)^{-\theta}$$

Firms use labor to produce differentiated products and meet the demand from local consumers, consumers from another province, and the government. The firm producing the variety z is subject to the following constraint:

$$(nC_{Ht} + (1-n)C^*_{Ht} + nG_{Ht}) \left(\frac{p_{ht}(z)}{P_{Ht}}\right)^{-\theta} \leq y_{ht}(z) = f(L_t(z))$$

There are two price setting scenarios controlled by the parameter α, the probability of price adjustment: flexible ($\alpha = 0$) and sticky (for example, $\alpha = 0.75$) prices.

There is a government that conducts fiscal and monetary policy and purchases goods in provinces. G_{Ht} is government spending per capita in the home province. It follows the exogenous AR(1) process with a parameter ρ_G. Local government demand for differentiated products has the same form as a private demand:

$$g_{ht}(z) = G_{Ht} \left(\frac{p_{ht}(z)}{P_{Ht}}\right)^{-\theta}$$

I start with complete markets. There are two types of budget policy that are relevant for the aggregate multiplier. First, the government may finance its purchases with lump-sum taxes. In this case, distortionary tax rate does not respond to government spending shock. An alternative is to consider "balanced budget" policy when distortionary tax rate increases to finance the increase in spending:

$$nP_{Ht}G_{Ht} + (1-n)P_{Ft}G_{Ft} = \tau_t \int W_t(x)L_t(x)dx$$

There are three options for monetary policy. The first is a standard Taylor rule policy when the central bank aggressively responds to inflation caused by government spending shock:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\phi_\pi \pi_t^{agg} + (1-\rho_i)\phi_y y_t^{agg} + \epsilon^m$$

Less responsive is the fixed real rate policy, when the central bank keeps the real rate fixed in response to the government spending shock. Finally, I consider the fixed nominal rate policy, when the nominal rate is maintained constant when the government spending shock occurs.

Next, I move to the case of the incomplete markets when only one noncontingent bond is traded across provinces. In this environment, the way spending is financed matters for the relative multiplier, since the risk is not completely shared across provinces. I consider two specifications of province budget constraint: locally and nationally financed government purchases.

IV.B Relative and Aggregate Multipliers

The unique equilibrium of the model is obtained with the methods of Sims (2001). The set of log-linearized conditions can be found in the Appendix Subsection VI.C. Then the quarterly data is simulated from the model and aggregated to annual frequency.

To compute the relative multiplier on the simulated by the model data, I follow Nakamura and Steinsson (2014) and take a linear approximation of dependent and independent variables in the regression:

$$\frac{Y_{it} - Y_{it-1}}{Y_{it}} = \alpha + \beta_R \frac{G_{it} - G_{it-1}}{G_{it}} + \delta_t$$

A linear approximation of the dependent variable is:

$$\frac{\frac{P_{Ht}Y_t}{P_t} - \frac{P_{Ht-1}Y_{t-1}}{P_{t-1}}}{\frac{P_{Ht-1}Y_{t-1}}{P_{t-1}}} = \frac{Y_t}{Y_{t-1}} \frac{\Pi_{Ht}}{\Pi_t} - 1 = \hat{y}_t - \hat{y}_{t-1} + \hat{\pi}_{Ht} - \hat{\pi}_t + h.o.t.$$

where $h.o.t.$ denotes "higher order terms". A linear approximation of the dependent variable is:

$$\frac{\frac{P_{Ht}G_{Ht}}{P_t} - \frac{P_{Ht-1}G_{Ht-1}}{P_{t-1}}}{\frac{P_{Ht-1}Y_{t-1}}{P_{t-1}}} = \frac{G_{Ht}}{Y_{t-1}} \frac{\Pi_{Ht}}{\Pi_t} - \frac{G_{Ht-1}}{Y_{t-1}} =$$
$$= \hat{g}_t - \hat{g}_{t-1} + \left(1 - \frac{C}{Y}\right)\left(\hat{\pi}_{Ht} - \hat{\pi}_t^W\right) + h.o.t.$$

The aggregate multiplier is computed by running the regression on aggregated data simulated by the model:

$$\frac{Y_t^{agg} - Y_{t-1}^{agg}}{Y_{t-1}^{agg}} = \alpha + \beta_A \frac{G_t^{agg} - G_{t-1}^{agg}}{Y_{t-1}^{agg}} + \epsilon_t$$

IV.C Calibration

I calibrate the standard parameters as in Nakamura and Steinsson, 2014. Differently from this paper, I calibrate a home-bias parameter, persistence of government spending, monetary policy rule and the size of the home region.

To calibrate a home-bias parameter, which is a proxy for the openness of the provinces, I use the results from the survey on interregional trade conducted by the Bank of Italy (Bentivogli et al. (2018)). The authors find out that the share of interregional exports in Italy is on average 44% of the regional value added. I assume that Italian provinces are as open as regions and set the home-bias parameter equal to 0.56. I calibrate the size of the home region equal to 0.01, which is approximately 1 over 94 (the number of provinces). These parameters suggest that the provinces are very small and very open economies.

Since the exogenous variation in government spending defined by city council dismissals in the empirical work does not follow a process with high persistence, the relative multiplier obtained in the previous section reflects the transitory nature of spending. I set the persistence parameter of the government spending process equal to 0.6.

The dataset I consider for the empirical estimation covers the periods when the lira was floating freely, and the Italian monetary policy was independent. According to De Arcangelis and Giorgio (1998), during the period 1989 - 1996 the targeting of interest rate on overnight loans best describes the monetary policy regime in Italy. Caputo and Diaz (2018) estimate the Taylor rule for Italy over the period 1981 - 1998:

$$i_t = \alpha + \rho i_{t-1} + \delta_\pi E_t \left[\pi_{t+j}\right] + \delta_y y_t$$

where the smoothing parameter $\rho = 0.879$, $\delta_\pi = 0.174$, $\delta_y = 0.0763$. In terms of the parameters in the model, this implies $\rho_i = 0.9$ $\phi_\pi = 1.7$ and $\phi_Y = 0.8$, - highly responsive monetary policy.

IV.D Results

Table 5 presents aggregate and relative multipliers computed for the case of the complete markets. Given the nature of price-setting and the persistence of the spending process, the relative multiplier remains the same and is independent of the aggregate policy. Since in this model provinces are homogenous in the response of output to aggregate shocks, time controls included in the regression when the relative multiplier is computed capture all the aggregate level movements.

The aggregate multiplier, in contrast, depends on the policy at the national level. Under sticky prices, monetary policy plays a central role in the effect of government spending. Under the Taylor rule, the central bank responds aggressively to the inflation cased by the government spending shock and increases the real interest rate. The higher real interest rate makes people consume less, and, therefore, counteracts the positive effect of the government spending shocks on output. If the real rate is maintained fixed, there is no "crowding-out" effect, and the output increases one-to-one in response to the fiscal shock. Finally, the most accommodative version of monetary policy, fixed nominal rate, leads to the "crowding-in" effect because the higher inflation pushes a real rate down. Under this policy, the aggregate multiplier exceeds 1, and this effect is the stronger the higher the persistence of spending is.

When prices are flexible, budget policy matters for the national multiplier. When distortionary taxes increase in the response to the spending shock, people give up a part of their labor income to finance government purchases and the aggregate multiplier gets lower in comparison with the lump-sum taxes case.

Nakamura and Steinsson, 2014 suggest to use the relative multiplier as a tool to distinguish between different modeling assumptions. For the case with Italy, the relative multiplier obtained in empirical section is closer to the multiplier generated by the model with a high degree of price rigidity. Therefore, the predictions about the aggregate multiplier are likely to be in line with the New-Keynesian model, and to depend on the monetary policy rule.

Table 5: Government Multiplier: Complete Markets

	Aggregate	Relative
Sticky Prices		
Taylor Rule	0.54	0.96
Constant real rate	1.00	0.96
Constant nominal rate	1.04	0.96
Constant nominal rate ($\rho_G = 0.8$)	1.25	0.92
Flexible Prices		
Constant income tax rates	0.39	0.39
Balanced budget	0.32	0.39

Note: The table presents the relative and aggregate government spending multipliers for output deflated by the regional CPI for the model of a monetary union under sticky and flexible prices. The first three rows differ only in the assumptions about monetary policy. The fourth row assumes different persistence of the government spending shock relative to the baseline parameter values. The fifth and sixth rows differ only in the budget policy being assumed.

Table 6 presents the multipliers generated under the assumption that markets are incomplete. In the absence of perfect insurance across provinces the relative multiplier depends on the way the spending is financed. Intuitively, if the government purchases within a province are financed by the whole country, households within a province are getting relatively wealthier. Since there is a home-bias in their consumption, they will spend the larger part of their wealth on the local goods, which makes the relative multiplier higher than in the case when the spending is financed by the households within a province only. The incomplete market version of the New-Keynesian model is the best to predict the nationally-financed relative multiplier estimated for Italy.

Table 6: Government Multiplier: Incomplete Markets

	Aggregate	Relative
Sticky Prices		
Complete markets	0.54	0.96
Incomplete markets, locally financed	0.47	0.96
Incomplete markets, nationally financed	0.47	0.98
Flexible Prices		
Complete markets	0.39	0.39
Incomplete markets, locally financed	0.39	0.45
Incomplete markets, nationally financed	0.39	0.45

Note: The table presents the relative and aggregate government spending multipliers for output deflated by the regional CPI for the model of a monetary union under sticky and flexible prices when markets are incomplete.

V Conclusions

This work analyzes the response of the output growth to the decrease in government purchases in Italy at differnet levels of aggregation. Accounting for the heterogeneity in response to aggregate shocks across provinces, I estimate the provintial level multiplier to be close to 1. This result may be reconciled with the national multiplier predicted by the New-Keynesian model, which generates a large multiplier when the monetary policy is unresponsive, and the persistence of spending process is high.

The relative multiplier I get has a specific nature. First of all, it is a contractionary multiplier since it is identified with exogenous cuts in spending. It could be that the output growth responds to the increase in government purchases with a different magnitude, so that the results from this work are valid only for one direction of spending. Secondly, in the data I consider, government purchases are outside-financed since local governments did not have the power to adjust taxes in response to the increase in spending. I expect the deficit-financed multiplier (an empirical counterpart of the locally-financed multiplier in the model) to be higher because agents within a province would anticipate the increase in taxes and would consume less in response to the spending shock. Moreover, the exogenous variations in spending process are transitory and the higher persistence is likely to make the multiplier lower. Finally, this work considers spending in infrastructure, and other types of spending may produce different multipliers.

The empirical results in this project are based on the assumption that if provinces can be devided into groups by the output growth response to aggregate shocks, these groups will be the same for the government spending response to aggregate shocks. This implies that provinces within the same group are homogenous in response of government spending to output growth. Although this assumption simplifies the empirical estimation, additional evidence is needed to justify it. One of the ways to do it would be to use the instrument for output growth in the equation for government spending to define groups and to compare the group membership with the one obtained from the reduced form equation for output growth.

Another potential extension would be to establish what determines the group membership. This could be done by running the regressions of group membership indicators on different provinces characteristics.

VI Appendix

VI.A Additional estimation results

Table 7: Public Spending Multplier: 2-10 Groups

	2	3	4	5	6	7	8	9	10
G(t)	1.79*	1.85**	0.66	0.67	0.99*	1.40***	1.27***	1.27**	1.22**
	[0.73]	[0.57]	[0.38]	[0.40]	[0.44]	[0.35]	[0.37]	[0.47]	[0.45]
G(t-1)	0.72*	0.77**	0.37*	0.36*	0.45**	0.51***	0.46***	0.45**	0.43**
	[0.31]	[0.24]	[0.15]	[0.15]	[0.16]	[0.13]	[0.13]	[0.15]	[0.15]
Y(t-1)	-0.12	-0.14	0.03	-0.01	0.06	0.05	0.07	0.08	0.10
	[0.07]	[0.07]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.05]	[0.05]
F	5.56	6.27	4.68	4.01	13.25	13.66	14.72	9.84	9.98
BIC	4.963	4.835	4.758	4.725	4.721	4.738	4.782	4.85	4.915

Note: Each column of the table presents the estimation results from the second step of IV regression (equation (10)) for the indicated number of groups. Reported in brackets are the standard errors clustered by region. Number of observations is 940 for each regression. The dependent variable is a year-on-year growth of value added. Control variables include the first difference of the number of people reported for mafia-related crime (up to two lags), two lags of the growth in per capita unemployment, the second and the third lags of city council dismissals. The forth row reports the F-statistic from the first stage ((9)). The fifth row reports the Baysean Information Criteria computed according to (11).

Table 8: Public Spending Multplier: 2-10 Groups. Exclusion restriction test

	2	3	4	5	6	7	8	9	10
G(t)	1.29*	1.30*	0.62	0.63*	0.89*	1.34***	1.22***	1.16***	1.30***
	[0.56]	[0.57]	[0.32]	[0.31]	[0.37]	[0.27]	[0.27]	[0.31]	[0.30]
G(t-1)	0.55*	0.59**	0.34**	0.34**	0.41**	0.50***	0.45***	0.46***	0.52***
	[0.22]	[0.22]	[0.13]	[0.12]	[0.14]	[0.12]	[0.11]	[0.11]	[0.11]
Y(t-1)	-0.10	-0.13*	0.04	0.01	0.05	0.05	0.06	0.07	0.09
	[0.06]	[0.06]	[0.04]	[0.04]	[0.05]	[0.06]	[0.05]	[0.05]	[0.05]
F	16.18	25.70	29.51	28.71	24.26	16.03	15.27	13.70	13.77
BIC	4.783	4.659	4.567	4.540	4.5396	4.558	4.606	4.662	4.719

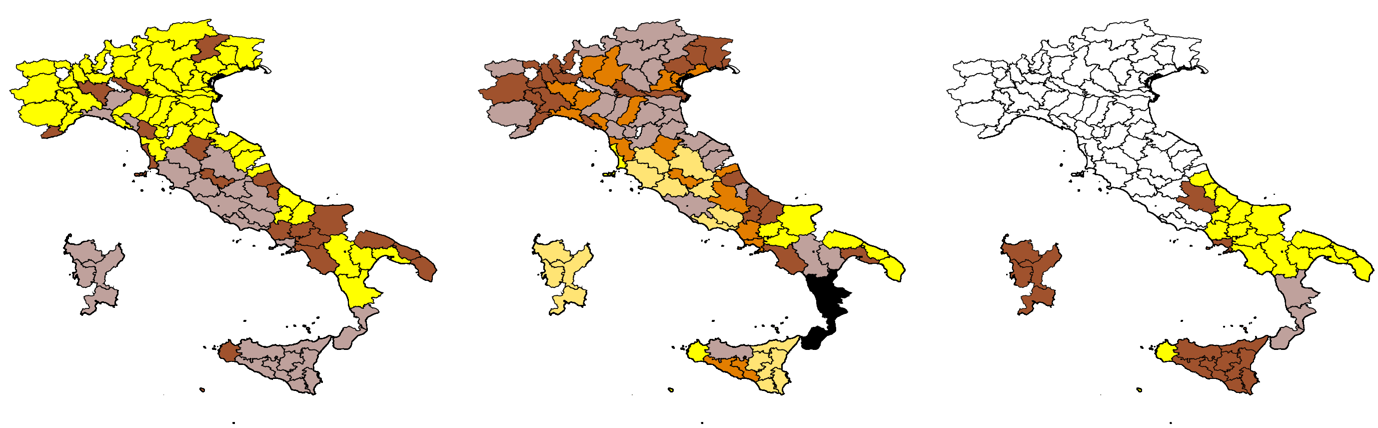
Note: Each column of the table presents the estimation results from the second step of IV regression (equation (10)) for the indicated number of groups. Reported in brackets are the standard errors clustered by region. Number of observations is 940 for each regression. The dependent variable is a year-on-year growth of value added. Control variables include two lags of the growth in per capita unemployment, the second and the third lags of city council dismissals. The forth row reports the F-statistic from the first stage ((9)). The fifth reports the Baysean Information Criteria computed according to (11).

Table 9: Public Spending Multplier: 2-8 Groups. Southern Provinces

	2	3	4	5	6	7	8
G(t)	2.21**	1.21**	1.09*	0.99	1.39*	1.59**	1.09
	[0.68]	[0.39]	[0.54]	[0.73]	[0.61]	[0.57]	[0.60]
G(t-1)	0.91**	0.56***	0.38*	0.36	0.49*	0.54**	0.38
	[0.31]	[0.17]	[0.18]	[0.24]	[0.21]	[0.20]	[0.21]
Y(t-1)	-0.22	-0.04	0.03	-0.04	-0.00	-0.08	-0.07
	[0.13]	[0.11]	[0.08]	[0.08]	[0.10]	[0.11]	[0.09]
F	6.50	5.32	5.66	3.48	2.89	2.30	4.20
BIC	7.179	7.121	7.189	7.337	7.572	7.852	8.176

Note: Each column of the table presents the estimation results from the second step of IV regression (equation (10)) for the indicated number of groups. Reported in brackets are the standard errors clustered by region. The sample is restricted to southern Italian provinces. Number of observations is 340 for each regression. The dependent variable is a year-on-year growth of value added. Control variables include the first difference of the number of people reported for mafia-related crime (up to two lags), two lags of the growth in per capita unemployment, the second and the third lags of city council dismissals. The forth row reports the F-statistic from the first stage ((9)). The fifth reports the Baysean Information Criteria computed according to (11).

Figure 1: Province classification



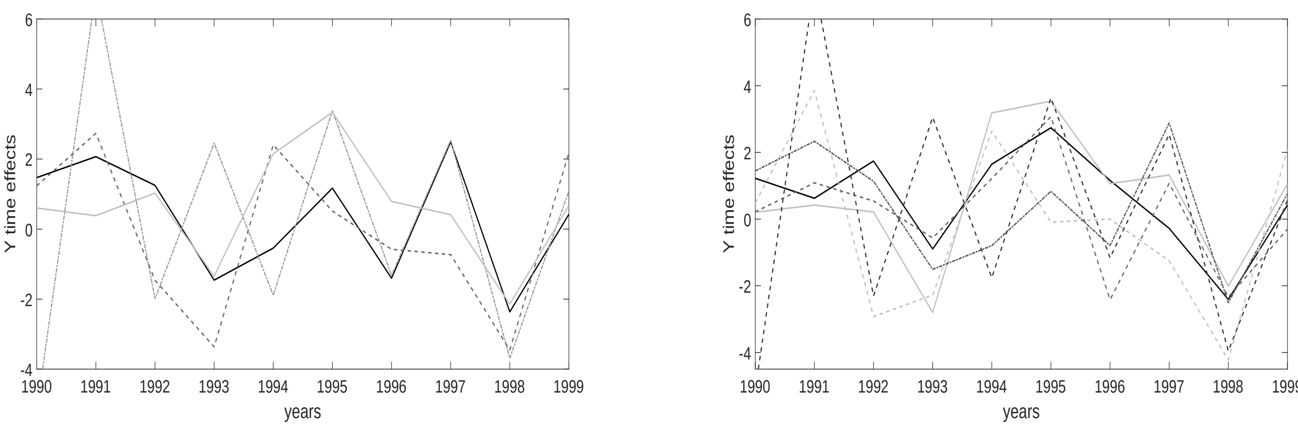
Note: The graphs show the group assignment across Italian provinces for the case with 3 groups (on the left), with 6 groups (in the middle), and with 3 groups when only southern provinces are included (on the right).

Table 10: Public Spending Multplier: 2-10 Groups. Provinces fixed effects

	2	3	4	5	6	7	8	9	10
G(t)	1.24	1.49*	1.39*	0.57	0.28	0.09	0.53	0.90*	1.18**
	[0.70]	[0.62]	[0.57]	[0.43]	[0.34]	[0.28]	[0.27]	[0.38]	[0.36]
G(t-1)	0.56*	0.64**	0.64**	0.35*	0.22	0.15	0.32**	0.35**	0.39**
	[0.27]	[0.23]	[0.22]	[0.17]	[0.14]	[0.11]	[0.10]	[0.12]	[0.12]
Y(t-1)	-0.20***	-0.21***	-0.19**	-0.09*	-0.12**	-0.13***	-0.09*	-0.14***	-0.19***
	[0.06]	[0.06]	[0.06]	[0.04]	[0.04]	[0.03]	[0.04]	[0.04]	[0.05]
F	4.05	4.65	4.44	4.36	3.62	6.71	7.58	7.60	7.06
BIC	5.943	5.824	5.779	5.750	5.763	5.784	5.853	5.896	5.969

Note: Each column of the table presents the estimation results from the second step of IV regression (equation (10)) for the indicated number of groups. Reported in brackets are the standard errors clustered by region. The sample is restricted to southern Italian provinces. Number of observations is 940 for each regression. The dependent variable is a year-on-year growth of value added. Control variables include the first difference of the number of people reported for mafia-related crime (up to two lags), two lags of the growth in per capita unemployment, the second and the third lags of city council dismissals. The forth row reports the F-statistic from the first stage ((9)). The fifth reports the Baysean Information Criteria computed according to (11).

Figure 2: Group specific time effects



Note: The plots present group-specific time effects obtained after the estimation of the baseline model (Table 7) for 4 (on the left) and for 6 (on the right) groups.

VI.B A Model of a Monetary Union: Calibration

Table 11: Calibration

Parameter	Definition	Value
	Fundamentals: Preferences	
σ	intertemporal elasticity of substitution	1
β	subjective discount factor	0.99
θ	elasticity of substitution across varieties	7
η	elasticity of substitution between home and foreign goods	2
ϕ_H	home-bias	0.56
ν	Frish elasticity of labor supply	1
	Fundamentals: Technology	
a	labor share	0.67
α	frequency of price change	0 or 0.75
n	size of the home region	0.01
	Aggregate Policy	
ρ_i	Taylor rule: smoothness	0.9
ϕ_π	Taylor rule: inflation	1.7
ϕ_Y	Taylor rule: output	0.8
ρ_G	persistence of government spending process	0.6
$\frac{\bar{G}}{\bar{Y}}$	Steady state level of government spending as a percent of GDP	0.2

VI.C A Model of a Monetary Union: Log-linearized equations

The model can be described with a linearized system of equations, where $\kappa = \frac{(1-\alpha)(1-\alpha\beta)}{\alpha}$; $\psi_v = \frac{1+\frac{1}{\nu}}{a} - 1$; $\zeta = \frac{1}{1+\psi_v\theta}$.

Home Consumption Euler equation:

$$-c_t + E_t c_{t+1} - \sigma i_t + \sigma E_t \pi_{t+1} = 0$$

Backus-Smith Condition:

$$E_t c_{t+1} - c_t^* - \sigma q_t = 0$$

Home and Foreign Philips Curves:

$$-\pi_{Ht} + \beta E_t \pi_{Ht+1} + \kappa\zeta(\frac{1}{\sigma}c_t + \psi_v y_t - p_{Ht} + \frac{\bar{\tau}}{1-\bar{\tau}}\tau_t) = 0$$
$$-\pi_{Ft} + \beta E_t \pi_{Ft+1} + \kappa\zeta(\frac{1}{\sigma}c_t^* + \psi_v y_t^* + q_t + \frac{\phi_H}{\phi_F}p_{Ht}\frac{\bar{\tau}}{1-\bar{\tau}}\tau_t) = 0$$

Home and Foreign Inflation:

$$-\pi_t + \phi_H \pi_{Ht} + \phi_F \pi_{Ft} = 0$$
$$-\pi_t^* + \phi_H^* \pi_{Ht} + \phi_F^* \pi_{Ft} = 0$$

Home and Foreign Resource Constraints:

$$y_t = \bar{C}\phi_H c_t + \bar{C}\frac{1-n}{n}\phi_H^* + \eta\bar{C}\frac{1-n}{n}\phi_H^* q_t - \eta\bar{C}(\phi_H + \frac{1-n}{n}\phi_H^*)p_{Ht} + g_{Ht}$$
$$y_t^* = \bar{C}\frac{n}{1-n}\phi_F c_t + \bar{C}\phi_F^* c_t^* + \eta\bar{C}\phi_F^* q_t + \eta\bar{C}(\frac{n}{1-n}\phi_F + \phi_F^*)\frac{\phi_H}{\phi_F}p_{Ht} + g_{Ft}$$

Home Relative Price:

$$p_{Ht} - \pi_{Ht} + \pi_t = p_{Ht-1}$$

Real Exchange Rate:

$$q_t = (\phi_H^* - \frac{\phi_H}{\phi_F}\phi_F^*)p_{Ht}$$

Home and Foreign Nominal Outputs:

$$ny_t = y_t + \pi_{Ht}$$
$$ny_t^* = y_t^* + \pi_{Ft}$$

Home and Foreign Production Functions:

$$y_t = aL_t$$
$$y_t^* = aL_t^*$$

Home and Foreign Production Real Wages (PPI as deflator):

$$w_t - p_{Ht} - \frac{1}{\sigma}c_t - \frac{1}{a\eta}y_t + p_{Ht} - \frac{\bar{\tau}}{1-\bar{\tau}}\tau_t = 0$$
$$w_t^* - p_{Ft} + q_t - \frac{1}{\sigma}c_t^* - \frac{1}{a\eta}y_t^* - q_t - \frac{\phi_H}{\phi_F}p_{Ht} - \frac{\bar{\tau}}{1-\bar{\tau}}\tau_t = 0$$

Home and Foreign Real Marginal Costs (PPI as deflator):

$$s_t + p_{Ht} - \frac{1}{\sigma}c_t - \psi_v y_t + p_{Ht} - \frac{\bar{\tau}}{1-\bar{\tau}}\tau_t = 0$$
$$s_t^* + p_{Ft} - q_t - \frac{1}{\sigma}c_t^* - \psi_v y_t^* - q_t - \frac{\phi_H}{\phi_F}p_{Ht} - \frac{\bar{\tau}}{1-\bar{\tau}}\tau_t = 0$$

Home and Foreign CPI Price Levels:

$$p_t - p_{t-1} = \pi_t$$
$$p_t^* - p_{t-1}^* = \pi_t^*$$

Home and Foreign Government Spending:

$$g_{Ht} = \rho_G g_{Ht-1} + \epsilon_t^g$$
$$g_{Ft} = \rho_G g_{Ft-1} + \epsilon_t^{g^*}$$

Taylor rule for Monetary Policy:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\phi_\pi(n\pi_t + (1-n)\pi_t^*) + (1-\rho_i)\phi_y(ny_t + (1-n)y_t^*) + \epsilon^m$$

If Balanced Budget Policy (with distortionary taxes) takes place, there is an additional balanced budget constraint:

$$\tau_t + n(w_t - p_{Ht}) + (1-n)(w_t^* - p_{Ft} + q_t) + \frac{n}{a}y_t + \frac{1-n}{a}y_t^* = ng_{Ht} + (1-n)g_{Ft}$$

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