Essays on Inflation Dynamics Estimation

by

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Abstract

Estimation of short-run inflation dynamics is important to policy makers for the effective implementation of monetary policy. My dissertation studies the estimation of inflation dynamics at the aggregate level by considering more disaggregated level data. The first chapter employs a regional framework to study the potential improvement of estimating the inflation dynamics in the US with regional variation and instrument selection. The second chapter switches the angle of disaggregate data by focusing on estimating sector inflation dynamics and implied aggregate inflation dynamics. The third chapter studies the inflation dynamics in the euro area by estimating country-specific inflation dynamics of each member state. All three chapters study the inflation dynamics in a hybrid New Keynesian Phillips curve and the many instruments issue is solved by instrument selection using a kernel-weighted Lasso method introduced in the first chapter.

The first chapter examines the inflation dynamics in a hybrid New Keynesian Phillips Curve (NKPC) that encounters the many instruments problem. Monte-Carlo simulations demonstrate that the NKPC can be better estimated in finite samples if the instruments are selected by a kernel-weighted Lasso method. In addition, I consider a disaggregated regional NKPC model and show that this can further help with the efficient estimation of national inflation dynamics. I apply these methods to US data and find that the inflation process is more forward-looking than typically found in other studies. I also find a statistically significant trade-off between national inflation and unemployment in the short run, that is only evident when using disaggregated data.

The second chapter examines inflation dynamics for US sectors with emphasis on the various pricing behavior across sectors. It estimates inflation dynamics for the aggregate US economy and for each separate sector. Sectors are assumed to have different pricing behavior and this feature is incorporated in the sector specific New Keynesian Phillips curve. In the model part, I derive the sector inflation dynamics in the NKPC model by assuming asymmetric behavior of the firms, and the result suggests that sector inflation should be examined in separate sector regressions. In the empirical part, I apply US quarterly sector data to estimate the disaggregate and aggregate New Keynesian Phillips curves. I discuss the sector specific results and explain the possible reasons for the heterogeneous behavior across sectors through international competition. More importantly, I find that disaggregate sector inflation dynamics can help uncover a significant relationship between inflation and unemployment at the aggregate level.

The third chapter empirically investigates inflation dynamics for the euro area in the presence of heterogeneous economic conditions across member states. It reviews the inflation dynamics since 2000 for the euro area as a whole and for individual euro area countries. Cross-country heterogeneity is considered and incorporated in separate national New Keynesian Phillips curves. Moreover, this paper highlights the improvement of the estimates of aggregate inflation dynamics through national estimates aggregation and instrument selection. In the empirical part, I apply monthly national and euro area data to estimate the national and euro-wide New Keynesian Phillips curves. I discuss country-specific inflation dynamics, but more importantly, I find that disaggregate national estimates can help uncover a significant relationship between inflation and unemployment in the euro area by reducing the standard errors of the implied parameters. Although the Phillips curve is not a sufficient tool to gauge inflation dynamics as already discussed in the literature, a more precise estimate of the relation still helps with monetary policy formation in the euro area for ECB and national central banks.

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Dedication

This thesis is dedicated to my grandpa, Li Chengxiang.

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Chapter 1

Estimating Short-run Inflation Dynamics with Disaggregate Information and Selected Instruments

1.1 Introduction

Short-run inflation dynamics are critical to the effective implementation of monetary policy and have received extensive attention in recent theoretical and empirical work. How a central bank decides between higher or lower inflation depends on the short-run trade-off between inflation and real activity, and also on the effect of expectations of future economic activity on current price settings. These two factors that importantly affect inflation dynamics can be examined using the “New Keynesian Phillips curve” (NKPC). The NKPC has gained early success in fitting empirical data, but recently economists observed a flatter Phillips curve [1]. The model’s fit deteriorates after the inclusion of the recent Great Recession into the sample; economists have observed that inflation has not fallen as much as the traditional Phillips curve predicts [2]. The rate of inflation fell far less over the period 2007-2013 than in the period 1979-1985, despite similar large increases in the unemployment rate [3]. Using traditional methods, the New Keynesian Phillips curve could not find a significant trade-off between inflation and unemployment during this period.

This paper improves the estimation of the New Keynesian Phillips Curve by introducing instrument selection and regional variation into the model. I show that the New Keynesian Phillips curve can be better estimated in finite samples with instruments selected by a kernel-weighted Lasso method. Moreover, I show that regional variation can further help with the efficient estimation of national inflation dynamics. I apply US metropolitan area data to estimate the disaggregated regional NKPC model, which results in two important findings. First, both the national and regional inflation process are more forward-looking than would be estimated without using instrument selection. Second, there exists a statistically significant trade-off between national inflation and unemployment when estimating regional data, including the Great Recession period.

There are two main reasons for considering instrument selection and disaggregate information in order to improve the estimation of inflation dynamics. First, instrument selection is important and necessary to guarantee an unbiased estimate in finite samples: the endogeneity problem is prevalent in the NKPC model and the instruments are lagged variables, so there are many choices of predetermined variables that could be used as instruments (see [4]; [5]). It is well known that the usage of many instruments can lead to finite sample instrumental variable (IV) estimates that are biased towards OLS[1]. Second, the introduction of regional variation improves estimation efficiency by enlarging the data set, and narrowing the confidence intervals of estimates. It is also interesting to consider the inflation dynamics at regional level since the underlying trade-off between inflation and unemployment is more stable at the regional level. A number of economists argue that the statistically insignificant trade-off between inflation and unemployment may be arising from the central bank's targeting a certain level of inflation [8]. The regional inflation rate, on the other hand, would be allowed to react more freely to changes in regional unemployment. By estimating the regional NKPC, one can get to know not only the regional inflation dynamics, but also the national inflation dynamics implied from the regional inflation behavior.

This paper contributes to improving the estimation of short-run inflation dynamics in three steps. First, I show that the many instrument issues can be solved by selecting

[1]See [6] and [7]

instruments using Lasso and kernel-weighted Lasso methods. As first introduced by [9], Lasso, short for Least Absolute Shrinkage and Selection Operator, automatically selects instruments without imposing any prior information on the original instrument set[2]. In addition, given the belief that more recent instruments contain more information than more distant ones [13], the kernel-weighted Lasso method is developed to select instruments with lag structure. This method is not limited to the linear New Keynesian models, but can be applied to any other linear time series models with endogeneity that may potentially need instrument selection. In the Monte-Carlo simulation, I show that finite sample bias is reduced and efficiency is improved when the estimators are obtained with selected instruments using kernel-weighted Lasso at both the national and regional levels.

Second, I derive a theoretical regional New Keynesian Phillips curve that incorporates staggered price adjustments and mixed pricing behavior of regional firms, following that of two seminal papers, [14]; [15]. The issue with many instruments still exists as the lagged regional variables enter the choice set of potential instruments. The introduction of more data cannot fix this issue, but rather introduces more instruments to the first stage of the model. The regional estimate is obtained

[2]There exists a vast literature of using Lasso to deal with endogeneity problems and select instruments. For example, [10] constructs the optimal instrument for each endogenous variable under many instruments setup. They contribute to the literature on IV estimation by considering the use of Lasso and post-Lasso for estimating the first-stage regression of endogenous variables on the instruments. The IV estimator based on using Lasso or post-Lasso is root-n consistent and asymptotically normal. [11] used an adaptive Lasso estimator to select strong instruments in the first stage, and used the selected instruments in the generalized empirical likelihood estimation. In another example, [12] with many moments in GMM estimation, where they achieved three goals in one step, including to distinguish and select valid and relevant moments, as well as to estimate parameters of interest.

by using the Metropolitan area data in the US in the regional NKPC model with instruments selected by kernel-weighted Lasso. The regional model estimation suggests that inflation is more forward-looking, as the impact of a unit change in future inflation expectation on current inflation is 0.75. In a model estimated with traditional method, this forward-looking impact is only 0.6.

Last, this paper shows how more precise and efficient national inflation dynamics can be inferred from the regional model, compared to the national inflation patterns obtained directly using national data. Previous literature has shown an insignificant relation between national inflation and unemployment when including the Great Recession. However, if the national inflation dynamics are estimated and inferred using regional data in a regional model, there is a significantly negative relation between inflation and unemployment. This helps to explain recent puzzling inflation behavior.

The paper proceeds as follows. Section 2 describes the estimation of the inflation dynamics in the classic hybrid NKPC model and introduces the econometric method. The Lasso and kernel-weighted Lasso methods are also described in this section to provide instrument selection. Section 3 extends the model to the regional level where a nation with a continuum of regions is assumed. This regional model allows for the same price rigidity and the proportion of backward-looking firms across regions. The instrument selection procedure is still necessary in the regional model where the many instruments issue is prevalent. Regional inflation and implied national inflation dynamics are estimated using the derived regional model accordingly. Section 4 explores the empirical study with US statistical metropolitan area data, and a full conclusion is presented in section 5.

1.2 National NKPC Estimation

In this section, the national New Keynesian Phillips curve will be introduced, and the econometric issues with estimating the NKPC model will be discussed. The kernel-weighted Lasso method will be presented to select instruments among the instrument set with a lag structure. The model can be estimated using the optimal instruments selected and constructed by applying the kernel weighted Lasso in the first stage.

1.2.1 Model Setup

The "New Keynesian Phillips curve" is derived from a model of staggered price adjustment, take from [16]. [14] added backward-looking pricing behavior in addition to the purely forward-looking NKPC and argued that this Phillips curve with hybrid pricing behavior could better fit the data. In this section, I focus on the hybrid national NKPC taking the following form:

$$\pi_t = c + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \alpha x_t + u_t \tag{1.1}$$

where π_t is the inflation rate of period t and x_t is the forcing variable of period t. In this paper, I am using the unemployment rate as the forcing variable. $E_t(\pi_{t+1})$ is the expectation of inflation rate of period $t+1$ given the information set of period t. Based on model (1.1), national inflation is determined by future inflation expectations, previous inflation, and real economic activity. The parameter γ_f measures the forward-looking behavior of national inflation, while γ_b measures the backward-looking behavior of inflation. A popular restriction, supported by both theory and empirical data, is that the inflation coefficients sum up to 1, i.e., $\gamma_f + \gamma_b = 1$. In addition, parameter α measures the trade-off between inflation and unemployment. Therefore, precise estimation of model (1.1) is important to understand inflation patterns as well as the trade-off between inflation and unemployment.

Notice that the expectation term $E_t(\pi_{t+1})$ is unobservable, and following the literature (see [17]) [3], it can be replaced by the realized inflation at the next period π_{t+1} with a one-period-ahead inflation forecasting error, as shown in the following equation:

$$\pi_{t+1} = E_t(\pi_{t+1}) + e_{t+1} \tag{1.2}$$

[3]There are two other approaches in the literature to deal with the unobserved expectation term, also documented in [17]. The first of the two is to assume the reduced-form dynamics of inflation can be represented by a finite-order VAR, and thus called VAR approach (see [18] and [19]). But this assumption can be restrictive. Another way is to use survey data to measure rational expectation [20], and there are two arguments against the use of survey data in this paper. First, survey data is potentially endogenous, depending on when the survey is collected and whether other third-party shocks can affect both the inflation and people's expectations in the survey. Also the survey data is not good proxy for rational expectations since people seldom have the incentive to consider actual expectation and measurement error issues will rise. Second, this paper is estimating disaggregated level NKPC model and no survey data will be available.

where e_{t+1} stands for the inflation forecast error and can only be determined by new information from period t to $t+1$. After replacement, model (1.1) is rewritten as

$$\pi_t = c + \gamma_f \pi_{t+1} + \gamma_b \pi_{t-1} + \alpha x_t + \tilde{u}_t.$$

where $\tilde{u}_t = u_t - \gamma_f e_{t+1}$. The NKPC model is potentially endogenous after the replacement of expected inflation rates. First, the unemployment rate is endogenous since a supply shock affects both the pricing behavior of firms, as well as the hiring process in the labor market. Also, future inflation rate π_{t+1} is correlated with the forecasting error e_{t+1}, shown in the measurement equation(1.2), and thus π_{t+1} is endogenous and correlates with the error term $\tilde{u}_t$.

A common identification strategy in the literature requires a structural error term in the national hybrid NKPC model (1.1), i.e. $E_{t-1}(u_t) = 0$. By excluding previous variables from the model, NKPC assumes current and future shocks are not affected by previous information. I use instrumental variables to deal with the endogeneity problem. More specifically, I use linear generalized method of moments (GMM, [21]) to estimate the parameters. Let Z_t stand for the potential instrument vector, and the unconditional moments are constructed as the following equation:

$$E[Z_t' \tilde{u}_t] = 0 \tag{1.3}$$

Given the identification strategy discussed above, lagged variables are valid instruments. At the same time, lagged variables are often believed to be relevant instruments due to the persistence of macro-economic variables. This property forms a specific lag structure of instruments that often appears in similar models with rational expectations. For example, if there are p series that are initially correlated with the inflation rate or unemployment rate, the instrument set Z_t will use from one period lag to M period lag of those p series. The instrument can be re-noted as $Z_{t,M}$, but for simplicity we stick to Z_t in this paper. In total, there are Mp instruments in the instrument set.

There is an infinite number of predetermined variables that can be used as instruments, and different results arise from different choices of instruments. The choice of M is rather arbitrary. Many macro-economic variables are persistent, and thus M can be as large as the length of the series T. The Newey-West truncation number [22] is one popular choice, and in the following simulations and empirical sections, I set M as the Newey-West HAC estimator truncation number. However, the direct use of the arbitrarily large instrument set can lead to substantial problems in finite samples: as a consideration of the limiting case where the number of instruments is the same as the sample size reveals. In that case the first-stage yields perfect fit, and so 2SLS is identical to OLS. Consequently, effective instrument selection is necessary to precise estimation. In the next section, I will discuss the econometric methods that will be used to select instruments from the original instrument set with lag structure.

1.2.2 Lasso and Kernel Weighted Lasso

We have discussed the necessity of selecting instruments. In this part, I show the procedure of instrument selection and estimation using Lasso type methods in the first stage. [4] By using Lasso, one can automatically select the most relevant instruments without requiring prior knowledge or making further restrictions on the instrument set. Start from a single endogenous variable, the first stage regression between the endogenous variable and all instruments take the following form:

$$x_t = Z_t \Pi + \varepsilon_t \tag{1.4}$$

where ε_t is assumed to be *i.i.d.* and normally distributed. The use of many instruments will over-fit the model, and make the fitted value of x and original x exactly the same. In reality, not every instrument in Z_t is helpful in explaining the exogenous variation in x_t, and thus deleting irrelevant instruments will improve the performance of the first stage estimator.

Assume that the instrument vector Z_t has a sparse structure. Thus, the parame-

[4] In the instrument selection literature, various shrinkage methods other than the Lasso have been used. For example, [23] considered an approach to instrument selection based on the boosting method. [24] used another way of implementing shrinkage method which is the use of ridge regression for estimating the first-stage regression. The IV estimation with Lasso shrinkage in the first stage has better performance than the other approaches in the sense that Lasso does not require a priori knowledge of the strongest instruments. As long as the estimator satisfies the sparsity assumption which will be specified later in the model section, Lasso can provide effective instrument selection without requiring any priori knowledge.

ters in the above equation(1.4) estimated with Lasso takes the following form:

$$\hat{\Pi}_{lasso} = \arg\min_{\Pi}[\frac{1}{T}\sum_{t=1}^{T}(x_t - Z_t\Pi)^2 + \lambda\|\Pi\|_1] \tag{1.5}$$

where $\|\Pi\|_1 = \sum_{j=1}^{Mp}|\Pi_j|$ and $\lambda \geq 0$ is a penalty parameter. The existence of the $l1-norm$ penalty term has the potential to shrink the absolute value of the coefficients toward zero. Due to the $l1-$geometry, the Lasso is performing variable selection in the sense that it can shrink the coefficients of irrelevant instruments to exactly zero. Also the tuning parameter can alter the estimation greatly. With a larger penalty parameter λ, more coefficients will be shrunken to zero. On the other side, a smaller λ will result in more non-zero coefficients. The choice of λ is based on the criterion that the Lasso variable selection should achieve the oracle property, under which circumstance the Lasso performs as well as if the true model is known. Other than that, as pointed by [9], the Lasso method requires initial standardization of the regressors, so that the penalization scheme is fair to all instruments. The instrument set Z_t should be normalized to have zero mean and unit variance. The normalized instruments will only be used for instrument selection, and after certain instruments are selected, I will use the original value of selected instruments to form the moments.

However, Lasso may not be optimal in selecting instruments with lag structure. Given the feature that more recent instruments contain more information than more distant ones, the kernel-weighted Lasso distinguishes instruments of different lags by imposing higher penalty loadings to instruments with more lags, instead of treating all instruments equally as in the Lasso (1.5). [13] proposed a generalized class of GMM estimators based on kernel weighted moment restrictions. According to his work, kernel weighting is one way to take care of the correlated moments in the lag structure and thus reduce the higher order bias of GMM estimators. Inspired by the kernel-weighting approach, the modified Lasso estimator with kernel weights in the first stage is:

$$\hat{\Pi}_{k-lasso} = \arg\min_{\Pi}[\frac{1}{T}\sum_{t=1}^{T}(x_t - Z_t\Pi)^2 + \lambda\|W_T^{-1}\Pi\|_1] \tag{1.6}$$

where more weights will be imposed on more recent instruments and thus less penalty in the kernel-weighted Lasso objective function. To do this, W_T is a $Mp \times Mp$ weighting matrix as $W_T = (w_M \bigotimes I_p)$ and w_M is a diagonal matrix:

$$w_M = diag(k(0), \cdots, k((M-1/M))'.$$

where $k(\bullet)$ is a monotonically decreasing kernel function and $k(0) = 1$. There are several well-known kernels such as the truncated kernel, the Bartlett kernel, the Parzen kernel and the Tukey-Hanning kernel. The instrument set Z_t is ordered from the most recent to most distant period. Notice that the weighting matrix W_T is constructed by the Kronecker product of a diagonal matrix w_M and identity matrix I_p. The identity matrix is to make sure that instruments of the same period have the same penalty loading, and the diagonal matrix w_M with non-increasing elements on diagonal manages to impose different weights to instruments of different lags. Also it is easy to show that Lasso is a special case of kernel-weighted Lasso as long as $W_T = I_{Mp}$. Therefore, the kernel-weighted Lasso is more flexible than the standard Lasso.

One can notice that both Lasso and kernel-weighted Lasso estimators in the first stage rely on the choice of the tuning parameter λ. The changes of tuning parameter could easily alter the selected instrument set. Ideally, the tuning parameter λ should be simultaneously chosen with solving the objective function (equation (1.5) and (1.6)). Using kernel-weighted Lasso estimator as an example, the idea of picking the tuning parameter is the following. Since a sufficient and necessary condition for the minimizer is attained in the kernel-weighted Lasso problem as in equation (1.6) is that 0 belongs to the sub-differential of the convex objective function in (1.6). Equivalently, it means

$$\frac{2}{T} \max_{1 \leq j \leq Mp} |\sum_{t=1}^{T} (x_t - Z_t \Pi) W_T^{(j)} Z_t^{(j)}| \leq \lambda$$

Define a random variable

$$\Lambda = \frac{2}{T} \max_{1 \leq j \leq Mp} |\sum_{t=1}^{T} \varepsilon_t W_T^{(j)} Z_t^{(j)}| \tag{1.7}$$

The value for λ is solved empirically by simulating the random variable Λ and the tuning parameter λ is set to bound Λ with a large probability:

$$\lambda = c \cdot \Lambda(1 - \alpha | Z_1, \cdots, Z_T) \tag{1.8}$$

where $\Lambda(1-\alpha|Z_1, \cdots, Z_T)$ is the $(1-\alpha)-$quantile of Λ conditional on the instrument set, and $c > 1$ is a constant. Thus λ can be chosen based on the distribution of the random variable Λ.

Following [25] and [10], λ can be attained by the simulation of the random variable Λ. According to equation (1.7) and (1.8), the distribution of Λ depends on the error term ε in the first stage (1.4). Given the assumption of the normal distributed error term ε_t, Λ follows a normal distribution as well. Therefore, with the observables Y, X and Z, we can first estimate the initial variance of ε by running the first-stage regression and estimate the unbiased variance of the residuals. This initial variance of ε can be used to calculate the kernel-weighted Lasso estimator in equation (1.6), and thus select the instruments with non-zero coefficients. The kernel-weighted Lasso estimator is updated by using the updated variance of ε calculated by running the first stage regression between endogenous variables and the selected instruments in the previous step. This procedure is repeated for several steps until the selected instrument set converges. In this paper, I repeat these step for 20 times since it generally provides a converging variance of ε and choice of tuning parameter. Then we can simulate the random variance Λ and pick the $(1-\alpha)-$quantile of Λ. Here I use $c = 2$ [5].

Notice that the first stage equation (1.4) requires a scalar endogenous variable x_t. The above procedure of estimating the Lasso and kernel-weighted Lasso estimators in the first stage is applied to every endogenous variable in the NKPC model (1.1). I allow the penalty parameter λ to be different for different endogenous variables.

Returning to the original goal, we try to form the optimal instruments for the moment conditions (1.3). We adopt a post-Lasso procedure that follows the suggestion of [10]: the penalty term will shrink all coefficients towards zero, including the active instrument coefficients. Instead of using $\hat{\Pi}_{klasso}$ directly, we run another OLS regression with endogenous variables on the selected instruments from the Lasso and kernel-weighted Lasso estimators. In order to reduce the bias, as well as to take advantage of the variable selection procedure, one can benefit by using post-Lasso to form optimal instruments. In particular, still using kernel-weighted Lasso method as an example

$$\tilde{x}_t = P_{Z_{t,S_{klasso}}} x_t$$

where $P_{Z_{t,S_{klasso}}}$ is the projection matrix of $Z_{t,S_{klasso}}$, and $Z_{t,S_{klasso}}$ stands for the instrument set selected by picking the non-zero coefficient instruments from the original instrument set.

Therefore, the parameters in the model (1.1) can be estimated by the GMM

[5] c may not always equal to 2. The larger c is, the larger penalizing power the kernel-weighted Lasso will have. In general, a larger c will harm the choice of the kernel-weighted Lasso instrument selection.

estimation using the moments:

$$E[\tilde{X}_t' \tilde{u}_t] = 0$$

where $\tilde{X}_t$ is the vector of optimal instruments.

1.2.3 Simulation Results

In order to check the performance of the instrument selection with kernel weighted Lasso, a simulation study will be provided in this section based on the hybrid national NKPC model with the coefficient restriction $\gamma_f + \gamma_b = 1$:

$$\pi_t = c + \gamma_f E_t(\pi_{t+1}) + (1 - \gamma_f)\pi_{t-1} + \alpha x_t + u_t \tag{1.9}$$

where the parameter of interest here is $\theta = (c, \gamma_f, \alpha)$, and the true values of the parameters are $\theta_0 = (0, 0.7, -0.3)$. In order to solve for the reduced-form dynamics of inflation rates and unemployment rates, a VAR(2) dynamics equation system is defined:

$$\pi_t = c_\pi + \xi_{\pi 1}\pi_{t-1} + \xi_{x1}x_{t-1} + \xi_{\pi 2}\pi_{t-2} + \xi_{x2}x_{t-2} + \varepsilon_{\pi t} \tag{1.10}$$

and

$$x_t = c_x + \eta_{\pi 1}\pi_{t-1} + \eta_{x1}x_{t-1} + \eta_{\pi 2}\pi_{t-2} + \eta_{x2}x_{t-2} + \varepsilon_{xt} \tag{1.11}$$

where the coefficients for the reduced-form of η is calibrated using inflation and unemployment series from 1960 to 2014. η is calibrated by the OLS estimator of equation

(1.11), and $(\eta_{\pi 1}, \eta_{x1}, \eta_{\pi 2}, \eta_{x2}) = (0.008, 0.976, 0.017, -0.030))$. The variance covariance matrix Ω of$(\varepsilon_{\pi t}, \varepsilon_{xt})$ is set $\Omega = ((0.133, 0.034)', (0.034, 0.049)')$, which is a typical estimate of the disturbance covariance matrix in reduced-form OLS regressions on the 1960-2014 sample, using inflation series with the unemployment rate as the forcing variable. The reduced-form dynamics of π_t can be solved using the known parameters following the AIM algorithm of [26]. This is the basic data generating process (DGP) of the two series: the inflation rate and the unemployment rate. The sample period $T = 75$ is chosen to be consistent with the sample size examining in the empirical study in later sections, and the truncation parameter $M = 6$.

The instrument set Z_t originally includes up to 6-period lag of inflation rates, unemployment rates and four other fixed series following a multinomial distribution. I start off by running plain linear GMM with all available instruments. Lasso and kernel-weighted Lasso are also used in the first stage to select instruments. Within the fixed DGP, three types of estimators of the national NKPC model are used for comparison, in terms of finite sample bias, median bias, mean square error as well as the empirical probability of true value included in the confidence intervals.

The method of picking the tuning parameter λ is already discussed in the previous section. In each loop of the simulation, we need to pick the tuning parameters λ for the Lasso and kernel-weighted Lasso estimation. Also in this model we have two endogenous variables, and the tuning parameter λ needs to be picked respectively for each endogenous variable.

Table 1 presents the simulation results of national NKPC model using DGP discussed above. First, in terms of finite sample property, the results estimated with selected instruments using Lasso or kernel weighted Lasso could benefit from significant bias reduction compared to the IV estimators using all available instruments. Second, the root mean square error (RMSE) column is calculated as the square root of the sum of mean bias square and variance of estimates. Instrument selection can help improve the root mean squared error of the estimates for γ_f. Third, the last column coverage is comparing the inference made by different estimators. Inference made by GMM estimators using all instruments is misleading since the empirical probability of true values being included in the confidence interval is not consistent with the significance level of the confidence intervals, and thus tests that use all instruments could worsen the inference. As shown in Table 1, coverage rates have been improved with instrument selection and estimates with instruments selected by kernel-weighted Lasso achieve the best performance among the three categories.

More specifically, the national model shows how inflation dynamics is affected by future expectations and unemployment rate. The forward-looking behavior of inflation can be measured by γ_f, and the estimator of γ_f performs best when using instruments selected via kernel-weighted Lasso method. The root mean squared error of the kernel-weighted Lasso method is the lowest (0.116) among the three compared methods. It is well known that more instruments can help improve the efficiency of estimation, however, this just leads to misleading confidence intervals in finite samples (shown in the column of the coverage rate). Root mean squared error is one of the criterion to assess the finite sample performance of the estimators, and the performance improved after selecting instruments using kernel-weighted Lasso. Meanwhile, the trade-off between inflation and unemployment is captured by the parameter α, and the finite sample bias of the kernel-weighted Lasso selected instruments is smallest (0.074) among the three estimates. Estimates with instruments selected by Lasso achieve the lowest root mean squared error.

However, in the national NKPC model, instrument selection by Lasso and kernel-weighted Lasso does not succeed in reducing the root mean squared error of the estimate for α. It is because, by selecting instruments, on the one hand, the estimation bias is reduced due to using fewer but better instruments, but on the other hand, fewer instruments will harm the efficiency of estimation. In the next section, more data will be introduced and efficiency will be improved due to a larger data set. The performance of kernel-weighted Lasso instrument selection can be further improved.

1.3 Regional NKPC Estimation

In this section, regional variation will be introduced, and a regional NKPC model will be derived to explore the regional inflation dynamics. The regional Phillips curve is important not only because it is interesting by itself, but also because it may give more information about the national Phillips curve.

Several papers in the literature have considered the importance of disaggregate information to help improving the estimation of the NKPC model. In one example, [27] made use of regional variations to distinguish the impacts of short-term and long-term unemployment on inflation rates. Originally the national short-term and long-term unemployment rates are highly correlated, and it is hard to directly distinguish the pressures each exerts on inflation. By introducing regional data, more variations are brought in to the closely co-moving series. [28] argued that the regional trade-off of inflation and unemployment is consistent, with the central banks trying to stabilize the national inflation.

Inspired by the literature, there are two reasons of considering the regional NKPC model. First, more data will be used for estimation, and resulting in a more efficient estimation. Second, the structural relationship between inflation and unemployment will be more significantly revealed at the regional level. At the national level, without considering the central bank, there exists a trade-off between the unemployment rate and the inflation rate. For instance, a positive shock to the labor market will lower the unemployment rate and increase the nominal wage. A higher nominal wage will result in higher prices of goods, and thus higher inflation in the economy. But this relationship applies only when there is no central bank trying to stabilize the inflation rate. In the United States, the Fed has dual mandates: to stabilize inflation and to maximize employment. The first mandate does not allow inflation to react freely with the changes in the unemployment rate. And with the central bank putting more weights on inflation stabilization, one can observe the relationship between inflation and unemployment become less significant.

All of this underscores the benefits of studying regional inflation dynamics. The rationale for the trade-off of regional inflation and unemployment is similar to the national case. However, given the fact that the country is comprised of many small regions, any regional shocks will not alter the central bank's policy decisions. The regional inflation is allowed to freely react to the changes in regional unemployment, while the structural relationship still exists at the regional level. Also, by bringing the regional variation into the model, one is allowed to estimate the coefficients more efficiently. The regional NKPC model not only reveals how the regional inflation dynamics look, but also implies more precise national inflation dynamics.

The regional NKPC model should be derived to incorporate the following characteristics in order to capture the benefits. First, regional and national factors should play independent roles in affecting regional inflation rates. For example, the regional shocks affect only regional variables, while national shocks affect both regional and national variables. Second, regional firms follow the staggered price adjustment and mixed pricing behavior: that is, whenever they have chances to update the price, a proportion of firms, will follow forward-looking behavior while the rest of them will follow backward-looking rule-of-thumb principles.

1.3.1 Regional New Keynesian Phillips Curve

In this part, a theoretical framework of the regional NKPC model will be derived. The model is an extension of previous work on the New Keynesian model in the open economy by [15] by adding the backward-looking pricing rules of firms into the regional model introduced in [14].

Suppose the national economy is modeled with a continuum of small regions, represented by the unit interval. The measure of each region is zero. Different regions are subject to different productivity shocks. Each region has a representative household and a continuum of firms producing a differentiated good, also represented by the unit interval. Compared to the rest of the nation, the performance of each single region does not have impact on the national economy. Also, each region is assumed to be symmetric in terms of identical consumer preferences and firm pricing behavior.

There will be a brief idea of how the regional NKPC is derived, and more detailed derivations are in the appendix. All variables of lower-case letters represent the log of the variables with upper-case letters. I discuss the macroeconomic variables in the home region H. All other variables with subscript $i \in [0, 1]$ refer to region i. Region F represents a general notation for all other regions $i \in [0, 1]$ outside of region H. Taking $P^i_{H,t}$ as an example, it represents the price index of goods produced in region H at period t but finally consumed by consumers in region i. The superscript H is omitted for notation simplicity. Also, the Law of One Price holds for prices of the same good consumed in different regions, i.e., $P^i_{H,t} = P_{H,t}$, and $p^i_{H,t} = p_{H,t}$. Thus the superscripts for price variables are omitted.

We assume that firms from region H set prices as follows. In each period, $1-\theta$ random selected firms will set new prices, while the rest of the firms do not adjust prices, with an individual firm's probability of re-optimizing in any given period being independent of the time elapsed since it last reset its price. Meanwhile, a fraction $1-w$ of the firms, which we refer to as forward-looking firms, choose the price that maximizes the current market value of the profits generated while that price remains effective. The remaining firms, of measure w, which we refer to as backward-looking, instead use a simple rule of thumb that is based on recent aggregate pricing behavior.

Suppose at period t and in region H, if the firm is "randomly selected" to reset its price, a forward-looking firm will choose the price $P^f_{H,t}$, while the backward-looking firm will pick $P^b_{H,t}$. By law of large numbers, the aggregate price level of goods produced in region H evolves as a combination of last period's price and the average of current rest prices, under a zero steady-state inflation assumption:

$$p_{H,t} = \theta p_{H,t-1} + (1-\theta)\bar{p}^*_{H,t} \tag{1.12}$$

where the index for newly set prices can be expressed as $\bar{p}^*_{H,t} = (1-w)p^f_{H,t} + wp^b_{H,t}$. The aggregate price level of goods produced in region i can be obtained in the same way, and thus the general notation $p_{F,t}$. Inflation of goods produced in region H is given by $\pi_{H,t} = p_{H,t} - p_{H,t-1}$, $\pi_{i,t} = p_{i,t} - p_{i,t-1}$ denotes the inflation of goods produced in region i, and $\pi_{F,t} = \int_0^1 \pi_{i,t} di$ denotes the inflation of goods produced outside home region. Notice that the regional CPI is defined as $p_t = (1-\alpha)p_{H,t} + \alpha p_{F,t}$, and regional inflation rate $\pi_t = (1-\alpha)\pi_{H,t} + \alpha\pi_{F,t}$, with the parameter α capturing the home region bias of household consumption.

Therefore, in order to discover the factors that could affect the regional inflation, one seeks to explain how firms from the home region and other regions will pick prices given their pricing behavior. For a forward-looking firm from region H, with the price rigidity, maximization over all expected discount future profits induces firms to take into account the probability that they will not be able to reset their prices optimally in the future. Let β denote the discount factor. The optimal price for a forward-looking firm can be expressed as follows in a finite-order linearization,

$$p^f_{H,t} = (1-\beta\theta)\sum_{k=0}^{\infty}(\beta\theta)^k E_t(\hat{mc}_{t+k} + p_{H,t+k}) \tag{1.13}$$

where $\hat{mc}_{t+k}$ denotes the difference between the real marginal cost at time $t+k$ and its steady state value, and the production function is Cobb-Douglas with labor elasticity 1. And it can be derived that

$$p^f_{H,t} - p_{H,t-1} = (1-\beta\theta)\hat{mc}_t + \pi_{H,t} + \beta\theta(p^f_{H,t+1} - p_{H,t}) \tag{1.14}$$

by shifting equation (1.13) forward by one period and taking rational expectations on both sides. Similarly, forward-looking firms from region i will set prices following:

$$p^f_{i,t} - p_{i,t-1} = (1-\beta\theta)\hat{mc}^i_t + \pi^i_{i,t} + \beta\theta(p^f_{i,t+1} - p^i_{i,t}) \tag{1.15}$$

On the other side, I assume that backward-looking firms obey a rule of thumb that has the following two features (Gali and Gertler, 1999): first, no persistent deviations between the rule and optimal behavior (i.e., in a steady state equilibrium the rule is consistent with the optimal behavior); (b) the price in period t given by the rule depends only on information dated $t-1$ or earlier. I also assume that the firm is unable to tell whether any individual competitor is backward-looking or forward-looking. All firms across the country can be potential competitors to a specific firm. Then firms from region H that follow the backward-looking rule will reset their price as

$$p^b_{H,t} = (1-\alpha)\bar{p}^*_{H,t-1} + \alpha\bar{p}^*_{F,t-1} + \pi_{t-1} \tag{1.16}$$

In other words, a backward-looking firm at t from region H sets its price equal to the average price set in the most recent price adjustments, with a correlation for regional inflation.

The hybrid regional NKPC can be obtained:

$$\pi_{it} = c + \gamma_f E_t(\pi_{i,t+1}) + \gamma_{b1}\pi_{i,t-1} + \gamma_{b2}\pi_{t-1} + \gamma_c\pi_t + \alpha_1 x_{it} + \alpha_2 x_t + u_{it} \tag{1.17}$$

where $i = 1, 2, \cdots, N$ and $t = 1, 2, \cdots, T$. N denotes the number of regions and T is the sample period. According to the regional Phillips curve, the current regional inflation rate depends on the future regional inflation expectation, previous regional and national inflation rates, current national inflation, as well as current regional and national unemployment rates. Unemployment rates move in opposite directions with the real marginal cost, and thus are used as a proxy. This pool regression model assigns independent roles to regional and national factors. More specifically, parameters γ_f, γ_{b1} and α_1 measure the effects of regional factors on the regional inflation rate, while γ_{b2} and α_2 measure the effects of national factors on the regional inflation rate. Moreover, the coefficients in front of inflation variables sum up to one: $\gamma_f + \gamma_{b1} + \gamma_{b2} = 1$ and this restriction is supported by the model and empirical data.

However, the regional NKPC model still encounters endogeneity and un-observability issues. Regional expectations of inflation rates cannot be observed by econometricians. There is a lack of valuable survey data tracking the inflation expectations at the regional level. By assuming the rational regional inflation expectation rate, one can replace the expectation term with its realization and impose an innovation term to the error term. Notice that the new error term including the innovation correlates with the realized future regional inflation rate. Besides, a regional shock in the local labor market that might both affect regional firms' pricing behavior and hiring process, and this causes the correlation between regional unemployment and inflation rates. Similar rationale applies to national shocks.

$$\pi_{it} = c + \gamma_f \pi_{i,t+1} + \gamma_{b1} \pi_{i,t-1} + \gamma_{b2} \pi_{t-1} + \gamma_c \pi_t + \alpha_1 x_{it} + \alpha_2 x_t + \tilde{u}_{it}$$

where

$$\tilde{u}_{it} = u_{it} + \gamma_f (E_t(\pi_{i,t+1}) - \pi_{i,t+1})$$

Therefore, the potential endogenous variables are $\pi_{i,t+1}, \pi_t, x_{it}$ and x_t. Dealing with the endogenous variables, the identification strategy is similar to that which was introduced in the national model. I assume that for any region i, the error term u_{it} does not depend on any previous information $E_{t-1}(u_{it}) = 0$. Under the rational expectations of regional firms, innovation term is not affected by previous information as well, and this implies $E_{t-1}(\tilde{u}_{it}) = 0$.

There is a large set of instruments available for the estimation of the regional model, and the many instruments issue is not solved by introducing regional variation to the model. This is because on one side, lagged variables are taken as instruments, and meanwhile, both regional and national series can be considered as relevant instruments which have broadened the instrument choice to a large extent. Instrument selection is still important and necessary in the estimation of the regional model, and the Lasso-type methods can be carried over from the national model.

1.3.2 Implications for the National NKPC model

The regional model discussed above is used to estimate the inflation dynamics, and more importantly, the national inflation dynamics is implied from the regional model. Assume that the national variables are weighted averages of corresponding regional variables:

$$\pi_t = \frac{1}{N} w_i \sum_{i=1}^{N} \pi_{it} \quad x_t = \frac{1}{N} \sum_{i=1}^{N} w_i x_{it}$$

where w_i refers to the weight of region i, $\sum_1^N w_i = 1$. Taking weighted average across regions on both sides of model (1.17), the national inflation dynamics can be implied as

$$\pi_t = \frac{c}{1-\gamma_c} + \frac{\gamma_f}{1-\gamma_c} E_t(\pi_{t+1}) + \frac{\gamma_{b1}+\gamma_{b2}}{1-\gamma_c}\pi_{t-1} + \frac{\alpha_1+\alpha_2}{1-\gamma_c} x_t + \frac{u_t}{1-\gamma_c} \tag{1.18}$$

This equation is called the implied national inflation dynamics in the following paper. By comparing to the national NKPC model, $\frac{\gamma_f}{1-\gamma_c}$ determines by how much proportion that the national inflation is forward-looking and $\frac{\alpha_1+\alpha_2}{1-\gamma_c}$ shows the trade-off between national inflation and unemployment. The coefficients of the implied national model estimated using regional data can be compared with the coefficients of the national model estimated using national data directly.

1.3.3 Simulation: Regional Model

The simulation study is based on model (1.17) with assumption that $\gamma_f + \gamma_{b1} + \gamma_{b2} + \gamma_c = 1$:

$$\pi_{it} = c + \gamma_f E_t(\pi_{i,t+1}) + \gamma_{b1}\pi_{i,t-1} + \gamma_{b2}\pi_{t-1} + \gamma_c\pi_t + \alpha_1 x_{it} + \alpha_2 x_t + u_{it} \qquad (1.19)$$

where the parameter of interest is $\theta_R = (c, \gamma_f, \gamma_{b1}, \gamma_{b2}, \alpha_1, \alpha_2)$, γ_c is determined due to the coefficient constraint: $\gamma_c = 1 - \gamma_f - \gamma_{b1} - \gamma_{b2}$. In the data generating process, we set the true value of parameter θ_R as $\theta_{R,0} = (0, 0.7, 0.3, 0, -0.3, 0)$. The reduced-form dynamics of regional inflation and unemployment are solved in the same way as shown in the national simulation study. Also, the national variables are calculated as simple averages of the regional variables. In this simulation, I generate the variables of 20 independent regions from the above setups.

To be consistent with real data, the length of the sample period is set to $T = 75$. Also we calculate the Newey-West HAC variance since we are using lagged variables in moment conditions. The lag truncation number is set as $M = 6$, and we thus use up to six lags of variables as instruments. In order to get a better comparison between the GMM estimates with all instruments and Lasso suggested instruments, we also include four other lagged random variables as instruments besides the lagged inflation rates and unemployment rates. In total, we use 72 potential instruments to estimate the regional NKPC (1.19).

The Monte-Carlo simulation results report the estimation statistics from 1000 repetitions. In Table 2-4, I report for each parameter, the true value, mean of the 1000 estimates, median of the 1000 estimates, standard deviations of estimates, root mean squared errors, and the coverage rates corresponding to each parameter. Note that the coverage rate is the probability that the true value of parameter is contained in the 95% confidence intervals. The confidence intervals are constructed using the asymptotic standard errors of the estimates. Also, each table is constructed by three parts: GMM estimates with all instruments, GMM estimates with instruments selected from Lasso, and GMM estimates with instruments selected from the kernel-weighted Lasso.

Table 2 to 4 provide the regional estimation results (1.17), implied national results (1.18) and the national estimation results (1.1), respectively. In general, GMM estimators with selected instruments outperform estimates with unselected instruments both in finite sample property and coverage rates of confidence intervals. Meanwhile, regional variation helps improve the efficiency of estimation in the regional model as well as the implied national model.

In order to discuss the finite sample performance of the estimators, I check the parameters in the three models respectively. In the regional NKPC model, for example, the estimates for forward-looking parameter γ_f are compared in terms of finite sample bias and root mean squared error. The GMM estimator with Lasso selected instruments can reduce the root mean squared error by roughly 5% (from 0.093 to

0.088), while the estimator with kernel-weighted Lasso selected instruments reduce the bias by 50% (from 0.093 to 0.047). This improvement in root mean squared error comes mainly from bias reduction after instrument selection, and at the same time, the efficiency of estimation is not affected after introducing regional variation. In the implied national model, GMM estimator of the implied forward-looking parameter $\frac{\gamma_f}{1-\gamma_c}$ in model (1.18) obtained from selected instruments using kernel weighted Lasso also has the smallest root mean squared error 0.076 among the three categories of estimates. The reduction of RMSE is applicable to the national NKPC model as well.

Other than the finite sample performance, the coverage rates of 95% confidence interval for the estimates using all instruments are misleading in the implied national model and the national model, meaning that the corresponding asymptotic distributions in the finite sample are not plausible. Although it might be true that the asymptotic standard error of the GMM estimators using all instruments is smaller due to the use of more instruments, the standard error calculated in the finite sample is not consistent with that calculated in infinite samples. Meanwhile, the coverage rates approach the ideal 95% as the instruments are selected by the Lasso-type methods. For example, for the estimate of forward-looking parameter $\frac{\gamma_f}{1-\gamma_c}$ in the implied national model, the coverage rate of the 95% confidence interval rises from 70.9% (calculated by the estimates with all instruments) to 86% (calculated by the estimates with kernel-weighted Lasso selected instruments). The improvement of the coverage also applies to the national model.

It is also interesting to compare the implied national results (as in table 3) with the real national results (as in table 4). As mentioned above, the regional NKPC model can not only allow us to explore the regional inflation dynamics and regional Phillips trade-off, but also to infer a more efficient national model. By comparing the estimates of the forward-looking parameter $\frac{\gamma_f}{1-\gamma_c}$ in the implied national and γ_f in the national models, the Lasso-type estimators can outperform the estimators without instrument selection in reducing mean bias, reducing root mean squared error, and improving the coverage. Moreover, the standard deviations of all estimates in the implied national model are significantly lower than those in the national model. For instance, if the instruments are selected by kernel-weighted Lasso, the standard deviation of the forward-looking parameter $\frac{\gamma_f}{1-\gamma_c}$ in the implied national model is 0.045, while the standard deviation of the forward-looking parameter γ_f in the national model is 0.099. In short, implied national estimates are more efficient than national estimates for all instrument selection methods. Therefore, I conclude that the regional variation can help improve the efficiency of the national inflation dynamics estimates.

1.4 Empirical Results

In this section, I apply the instrument selection methods to the US metropolitan area data and estimate the regional New Keynesian Phillips curve. The inflation dynamics in the regional, implied national and national models will be shown respectively.

1.4.1 Data

For the regional NKPC model, the data source is mainly from Bureau of Labor Statistics. The national and regional New Keynesian Phillips curves are both estimated over the sample periods from the year 1990 to 2014 based on a semi-annual frequency. The Consumer Price Index (CPI) excluding food and energy is used as a measure for price and hence is used to calculate the inflation series. Also, we use the civilian unemployment rate as the forcing variable in the regional model. Moreover, the wage rate series is also taken as potential instruments.

I examined 23 large metropolitan areas (MSA) for the United States. The choice of MSA follows [27] except that Washington-Baltimore area is not included in the data since the regional data are only available within a short time series(after 2000). The metropolitan areas we consider are New York-Northern New Jersey-Long Island, Philadelphia-Wilmington-Atlantic City, Boston-Brockton-Nashua, Pittsburgh, Chicago-Gary-Kenosha, Detroit-Ann Arbor-Flint, St. Louis, Cleveland-Akron, Minneapolis-St. Paul, Milwaukee-Racine, Cincinnati-Hamilton, Kansas City, Dallas-Fort Worth, Houston-Galveston-Brazoria, Atlanta, Miami-Fort Lauderdale, Los Angeles-Riverside-Orange County, San Francisco-Oakland-San Jose, Seattle-Tacoma-Bremerton, San Diego, Portland Salem, Honolulu, and Denver-Boulder-Greeley.

Therefore, in the regional data set, I explore the inflation and unemployment series over 50 sample periods, 23 regions as well as the nation. Notice that the national variables are obtained through the national averages of all regions across the country. The chosen regions in the data account for around 55-60% of GDP in US in 2015. It is reasonable to assume all other regions should perform similar to the 23 regions examined in the data. Also the instruments are formed by up to M-lags of inflation, unemployment, employment growth rate and wage inflation rate. M is picked by the Newey-West truncation number, which is set to 6 in the data.

1.4.2 Results

Tables 5-7 show the regional results based on equation (1.17), the implied national results from the regional model (1.18), and the national results based on equation (1.1). As discussed, the series of previous periods can be treated as valid and relevant instruments due to the persistent effects of macro-economic variables and the independence between innovations and past information. Three categories of estimates are compared: the GMM estimates with all instruments and with optimal instruments formed by Lasso and kernel-weighted Lasso respectively.

There are several interesting findings by comparing the three tables. First, the regional results shown in table 5 suggest that the inflation rate is more forward-looking in the regional level. The estimates with selected instruments imply a more forward-looking behavior of regional inflation dynamics than the estimates without instrument selection. Estimation using all instruments suggests that roughly 60% of the regional inflation is driven by future regional expectations, while the estimation using kernel-weighted Lasso selected instruments shows that the regional inflation is around 70%-75% driven by expectations. Meanwhile, table 5 also shows that the role of previous national inflation (as estimated by γ_{b2}) becomes insignificant when the model is estimated with selected instruments. In short, the IV estimators using selected instruments suggest that regional inflation is more forward-looking, and regional factors play a more important role than the national factors. Meanwhile, the regional NKPC model can also reveal the trade-off between the inflation and unemployment rates.

Second, the implied national model estimates derived from the regional model show a significant negative relation between inflation and unemployment. This finding is an very important contribution of the paper. The regional NKPC can be used to explain recent inflation behavior after the Great Recession. Without introducing regional variations into the model, the national estimates could not show the negative relationship even after selecting the instruments (as shown in table 7).

Lastly, by comparing the national estimates and the implied national estimates, as in tables 6 and 7, the implied national estimates are more efficient than the national estimates, and therefore, one can obtain a narrower confidence interval from the implied national model. For instance, in table 7, the estimate of α in the national model has a 95% confidence interval of $[-0.0216, 0.1084]$ with instruments selected by Parzen kernel-weighted Lasso method. While the estimate of $\frac{\alpha_1+\alpha_2}{1-\gamma_c}$ using the same instrument selection method in table 6 has a 95% confidence interval of $[-0.0356, -0.0084]$. The way of revealing the significant trade-off in the implied national model is through efficiency improvement.

1.5 Conclusion

This paper examines the estimation of inflation dynamics with selected instruments and regional data. The set of potential instruments is large compared to the sample size due to the use of lagged variables. The benefit of selecting instruments is substantial in finite samples. Also a kernel-weighted Lasso method is specified to deal with the lag structure in the instrument set. By taking into account that more recent variables contain more information, the kernel-weighted Lasso selected instruments can outperform the plain Lasso method. Finite sample bias and inference are shown to be improved by selected instruments in Monte-Carlo simulations.

Moreover, regional variation is introduced to improve the efficiency of estimation. A theoretical model at the regional level is derived by following previous work combining the multiple-region framework and firm's hybrid pricing behavior. The regional model estimate can not only show the regional inflation dynamics, but also imply a more efficient national estimate. In the empirical work, I show that both national and regional inflation dynamics are more forward-looking than would be estimated without instrument selection. Meanwhile, there exists a negative relation between regional inflation and unemployment. In addition, the relation between national inflation and unemployment is significantly negative if estimated using regional data. Therefore, regional New Keynesian Phillips curve can be considered as a direction to try to explain the puzzling inflation behavior after the Great Recession.

Future work could consider inflation dynamics across different sectors. Different from the regional NKPC model, where firms from different regions in a country are assumed to be symmetric in terms of price adjustment speed, the sector inflation dynamics can also allow variations across sectors. Price rigidities can be different across sectors, and the proportion of forward and backward-looking firms can vary across sectors as well. Sector inflation dynamics are important not only because it can show how sectoral inflation rates differ from one another, but also because it can provide more information for understanding national inflation dynamics.

Table 1.1: National NKPC Simulation DGP 1

	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
All Instruments								
Const.	0.000	0.002	0.003	0.002	0.003	0.143	0.143	0.680
γ_f	0.700	0.573	0.572	-0.127	-0.128	0.074	0.147	0.239
α	-0.300	-0.108	-0.115	0.192	0.185	0.222	0.293	0.540
Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	-0.003	-0.005	-0.003	-0.005	0.199	0.199	0.891
γ_f	0.700	0.573	0.566	-0.127	-0.134	0.070	0.145	0.538
α	-0.300	-0.174	-0.175	0.126	0.125	0.230	0.262	0.864
Kernel-weighted Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.006	0.012	0.006	0.012	0.373	0.373	0.932
γ_f	0.700	0.626	0.617	-0.074	-0.083	0.089	0.116	0.866
α	-0.300	-0.226	-0.223	0.074	0.077	0.330	0.338	0.954

Notes: for each instrument selection process, the table reports the true values of the parameters, the mean of estimates, the median of estimates, standard deviations of estimates, root mean squared errors(RMSE) and coverage rates. The coverage rates are the empirical probabilities that the 95% confidence interval contains the true parameter.

Table 1.2: Regional NKPC Simulation

All Instruments								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.001	0.001	0.001	0.001	0.019	0.019	0.985
γ_f	0.700	0.617	0.615	-0.083	-0.085	0.042	0.093	0.985
γ_{b1}	0.300	0.317	0.317	0.017	0.017	0.016	0.023	0.744
γ_{b2}	0.000	0.067	0.067	0.067	0.067	0.043	0.079	0.996
α_1	-0.300	-0.529	-0.531	-0.229	-0.231	0.156	0.277	0.992
α_2	0.000	0.395	0.397	0.395	0.397	0.163	0.427	0.964
Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.000	0.000	0.000	0.000	0.022	0.022	0.991
γ_f	0.700	0.623	0.622	-0.077	-0.078	0.042	0.088	0.993
γ_{b1}	0.300	0.315	0.315	0.015	0.015	0.016	0.022	0.795
γ_{b2}	0.000	0.062	0.062	0.062	0.062	0.043	0.075	0.999
α_1	-0.300	-0.513	-0.515	-0.213	-0.215	0.154	0.263	0.998
α_2	0.000	0.351	0.354	0.351	0.354	0.169	0.390	0.985
Kernel-weighted Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.000	0.000	0.000	0.000	0.035	0.035	0.981
γ_f	0.700	0.639	0.645	-0.061	-0.055	0.045	0.047	0.999
γ_{b1}	0.300	0.310	0.310	0.010	0.010	0.016	0.016	0.915
γ_{b2}	0.000	0.051	0.045	0.051	0.045	0.044	0.046	0.993
α_1	-0.300	-0.477	-0.455	-0.177	-0.155	0.162	0.166	1.000
α_2	0.000	0.253	0.274	0.253	0.274	0.205	0.207	0.991

Notes: for each instrument selection process, the table reports the true values of the parameters, the mean of estimates, the median of estimates, standard deviation of estimates, root mean squared errors(RMSE) and coverage rates. The coverage rates are the empirical probabilities that the 95% confidence interval contains the true parameter.

Table 1.3: Implied National NKPC Simulation

	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
All Instruments								
Const.	0.000	0.001	0.001	0.001	0.001	0.019	0.019	0.979
$\frac{\gamma_f}{1-\gamma_c}$	0.700	0.617	0.615	-0.083	-0.085	0.042	0.093	0.709
$\frac{\alpha_1+\alpha_2}{1-\gamma_c}$	-0.300	-0.134	-0.128	0.166	0.172	0.120	0.205	0.847
Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.000	0.000	0.000	0.000	0.022	0.022	0.983
$\frac{\gamma_f}{1-\gamma_c}$	0.700	0.623	0.622	-0.077	-0.078	0.042	0.088	0.773
$\frac{\alpha_1+\alpha_2}{1-\gamma_c}$	-0.300	-0.162	-0.152	0.138	0.148	0.130	0.190	0.892
Kernel-weighted Lasso								
	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
Const.	0.000	0.000	0.000	0.000	0.000	0.035	0.035	0.965
$\frac{\gamma_f}{1-\gamma_c}$	0.700	0.639	0.645	-0.061	-0.055	0.045	0.076	0.860
$\frac{\alpha_1+\alpha_2}{1-\gamma_c}$	-0.300	-0.224	-0.201	0.076	0.099	0.178	0.193	0.956

Notes: for each instrument selection process, the table reports the true values of the parameters, the mean of estimates, the median of estimates, standard derivation of estimates, mean square errors(MSE) and coverage rates. The coverage rates are the empirical probabilities that the 95% confidence interval contains the true parameter.

Table 1.4: National NKPC Simulation: from Regional Data

	True Value	Mean	Median	Mean Bias	Median Bias	Std.Error	RMSE	Coverage
All Instruments								
Const.	0.000	0.000	-0.001	0.000	-0.001	0.033	0.033	0.657
γ_f	0.700	0.563	0.562	-0.137	-0.138	0.075	0.156	0.203
α	-0.300	-0.138	-0.140	0.162	0.160	0.243	0.293	0.562
Lasso								
Const.	0.000	0.001	0.000	0.001	0.000	0.049	0.049	0.877
γ_f	0.700	0.568	0.565	-0.132	-0.135	0.072	0.150	0.482
α	-0.300	-0.175	-0.171	0.125	0.129	0.263	0.292	0.844
Kernel-weighted Lasso								
Const.	0.000	-0.004	-0.001	-0.004	-0.001	0.102	0.102	0.926
γ_f	0.700	0.629	0.620	-0.071	-0.080	0.099	0.122	0.842
α	-0.300	-0.230	-0.226	0.070	0.074	0.480	0.485	0.936

Notes: for each instrument selection process, the table reports the true values of the parameters, the mean of estimates, the median of estimates, standard derivation of estimates, mean square errors(MSE) and coverage rates. The coverage rates are the empirical probabilities that the 95% confidence interval contains the true parameter.

Table 1.5: Regional Empirical Results

	Const.	γ_f	γ_{b1}	γ_{b2}	α_1	α_2
All instruments						
Estimates	0.0431	0.6074	0.2518	0.1408	-0.0567	0.0494
Std.Error	0.0419	0.0582	0.0379	0.0621	0.0116	0.0145
Lasso						
Estimates	0.1133	0.6889	0.2318	0.0793	-0.0281	0.0094
Std.Error	0.0441	0.0945	0.0506	0.0752	0.0171	0.0195
Kernel-weighted Lasso–Tukhan						
Estimates	0.1277	0.7141	0.2113	0.0745	-0.0231	0.0018
Std.Error	0.0444	0.0983	0.0491	0.0761	0.0175	0.0199
Kernel-weighted Lasso–Barlett						
Estimates	0.1280	0.7206	0.2115	0.0679	-0.0231	0.0016
Std.Error	0.0456	0.1104	0.0489	0.0784	0.0183	0.0209
Kernel-weighted Lasso–Parzen (most preferred)						
Estimates	0.1326	0.7482	0.1962	0.0556	-0.0202	-0.0018
Std.Error	0.0447	0.1041	0.0498	0.0767	0.0184	0.0207
Kernel-weighted Lasso–kBias						
Estimates	0.1326	0.7532	0.1982	0.0486	-0.0198	-0.0022
Std.Error	0.0448	0.1045	0.0494	0.0765	0.0181	0.0205

Notes: The table shows the estimates of regional NKPC model for GMM with all instruments, Lasso selected instruments and kernel-weighted Lasso selected instruments. The asymptotic standard errors are also provided.

Table 1.6: Implied National Empirical Results

	Const.	$\frac{\gamma_f}{1-\gamma_c}$	$\frac{\alpha_1+\alpha_2}{1-\gamma_c}$
All instruments			
Estimates	0.0431	0.6074	-0.0074
Std.Error	0.0418	0.0505	0.0064
Lasso			
Estimates	0.1133	0.6889	-0.0187
Std.Error	0.0430	0.0700	0.0065
Kernel-weighted Lasso–Tukhan			
Estimates	0.1277	0.7141	-0.0213
Std.Error	0.0440	0.0680	0.0067
Kernel-weighted Lasso–Barlett			
Estimates	0.1280	0.7206	-0.0215
Std.Error	0.0446	0.0749	0.0068
Kernel-weighted Lasso–Parzen (most preferred)			
Estimates	0.1326	0.7482	-0.0220
Std.Error	0.0440	0.0708	0.0068
Kernel-weighted Lasso–kBias			
Estimates	0.1326	0.7532	-0.0220
Std.Error	0.0445	0.0704	0.0069

Notes: The table shows the estimates of implied national NKPC model for GMM with all instruments, Lasso selected instruments and kernel-weighted Lasso selected instruments.

Table 1.7: National Empirical Results

All instruments			
	Const.	γ_f	α
Estimates	-0.2450	0.5044	0.0500
Std.Error	0.3040	0.1846	0.0551
Lasso			
Estimates	-0.4297	0.5279	0.0658
Std.Error	0.2595	0.1335	0.0466
Kernel-weighted Lasso–Tukhan			
Estimates	-0.4083	0.6065	0.0631
Std.Error	0.2607	0.1468	0.0469
Kernel-weighted Lasso–Barlett			
Estimates	-0.2928	0.6314	0.0434
Std.Error	0.1831	0.1331	0.0325
Kernel-weighted Lasso–Parzen (most preferred)			
Estimates	-0.2928	0.6314	0.0434
Std.Error	0.1831	0.1331	0.0325
Kernel-weighted Lasso–kBias			
Estimates	-0.4083	0.6065	0.0631
Std.Error	0.2607	0.1468	0.0469

Notes: The table shows the estimates of national NKPC model for GMM with all instruments, Lasso selected instruments and kernel-weighted Lasso selected instruments.

Chapter 2

Sector Inflation Dynamics

2.1 Introduction

The first chapter argues that regional variation can help improve the estimation of New Keynesian Phillips curve by introducing more observations (also see [27]). It shows that using traditional methods, New Keynesian Phillips curve could not find a significant trade-off between inflation and unemployment with recent Great Recession period included in the sample. Instead, by introducing instrument selection and regional variation into the model, the estimation of NKPC can be improved and better implemented. While this chapter switches the focusing angle to the argument that estimation of aggregate inflation dynamics can be improved by considering disaggregated sector dynamics. On the other hand, the inflation dynamics across sectors possess various behavior, and in particular, this paper focuses on improving the estimation of the New Keynesian Phillips curve by considering disaggregated sector data with instrument selection procedures applied in the estimation. A growing body of literature has discussed the potential gains of understanding the total inflation dynamics from estimating disaggregate sector level data. [29] discuss that one potential explanation for the weak performance of Phillips curve is that measures of core inflation track a wide array of goods and services whose prices change in response to different sectors. They argue that the influence of resource gap factors, such as the difference between the measured unemployment and its "natural" rate, may affect the costs of services more directly and substantially than the costs of goods. They demonstrate strong evidence and show that, while services inflation depends on long-run inflation expectations and the degree of slack in the labor market, goods inflation depends on short-run inflation expectations and import prices. Moreover, [30] show that they could improve the forecast of aggregate inflation by forecasting each subcomponent, goods and services, respectively. Similarly, [31] discuss the measurement of trend inflation can be improved by using disaggregated data on sectoral inflation.

The reason to consider instrument selection is to reduce finite sample bias in each separate regression, similar to that in the national and regional cases (see [4]; [5];[6];[7]). There are two main reasons for considering disaggregated sector information in this chapter. First, sector inflation dynamics are often driven by different processes, and estimating sector inflation dynamics might shed light on divergent movements in different sectors. [32] identifies a shift in 1994 in the gap between goods and services inflation and implicitly concludes that goods and services inflation are influenced by different factors. Also the work of [33] finds that flexible-price inflation is more responsive to the degree of economic slack than sticky-price inflation, while sticky-price inflation is more responsive to inflation expectations than flexible-price inflation. The results of existing literature indicate that variables can have markedly different explanatory power for price movements of different sectors. Second, the introduction of sector information improves the estimation efficiency of aggregate inflation dynamics by enlarging the data set and reducing the standard errors of implied aggregate inflation dynamics coefficients. Thus the estimation of aggregate inflation dynamics can be further improved by averaging separate sector inflation dynamics. It is pointed out in the literature that variables may become less informative when used directly to explain movements in inflation at the aggregate level (see [30], [34]).

The estimation of aggregate inflation dynamics is improved in the following three steps. First, I show that divergent price movements across sectors are governed by different processes in a theoretical sector New Keynesian Phillips curve. Firms across different sectors are allowed to have various speeds of price adjustment and pricing strategies, and thus a sector NKPC is derived to demonstrate inflation dynamics in each sector. To obtain sector inflation dynamics, we need to estimate separate sector regressions, which may encounter many instrument issues with lagged sector variables used as instruments. This is a similar case to the national inflation dynamics estimation discussed in the first chapter, and the kernel-weighted Lasso method is applied to select instruments with lag structure and reduce finite sample estimation bias.

Second, based on sector specific estimation results, the aggregate inflation dynamics can be implied more precisely and efficiently by taking weighted averages of each sector inflation dynamics. The previous literature has shown an insignificant relation between aggregate inflation and unemployment during the great recession [2]. However, if the aggregate inflation dynamics are estimated and inferred using sector data in separate sector models, this paper shows that there exists a statistically significant trade-off between inflation and unemployment.

Third and last, I estimate sector inflation dynamics individually and find empirical evidence of previous assumptions that price movements across sectors are affected by different factors. On average, inflation dynamics in services sectors are more affected by local labor market conditions while those in goods sectors rely more on global competition. Services sectors are more sticky-priced compared to goods sectors, and I find that firms in services sectors are more forward-looking compared to firms in goods sectors.

The paper proceeds as follows. Section 2 derives the sector level New Keynesian Phillips curve model where a nation with a continuum of sectors is assumed. Each separate sector model allows for different price rigidities and different proportions of backward-looking firms across sectors. Sector inflation and implied aggregate inflation dynamics are estimated and compared to the aggregate inflation dynamics. The estimation of each sector NKPC and also the aggregate NKPC needs to deal with many instruments issues since lagged variables are considered as potential instruments. Section 3 describes the econometric methods used for instrument selection. The Lasso and kernel-weighted Lasso methods are introduced in the first chapter and will be used for instrument selection in this section. Section 4 explores the empirical study with US sector data. Implied aggregate inflation dynamics as well as separate inflation dynamics will be estimated and discussed. A structural break in the sample will also be considered as an extension of the empirical study, and a full conclusion is presented in section 5.

2.2 Model Structure

In this section, I will derive the model specification of the sector NKPC following the spirit of [14] and [15], which will be used in separate sector regressions and imply aggregate results. Suppose the aggregate economy is modeled with a continuum of small sectors, represented by the unit interval $[0, 1]$. Different sectors are subject to imperfectly correlated productivity shocks. Each sector has a representative household and a continuum of firms producing a differentiated good, also represented by the unit interval. Compared to the rest of the economy, the performance of each sector does not have any impact on the aggregate economy. Also, each sector is assumed to be asymmetric in terms of divergent firms' pricing behavior across sectors.

I discuss the above macroeconomic variables in a randomly selected small sector A. Sector B represents a general notation for all other sectors $i \in [0, 1]$ other than sector A. Taking $C^i_{A,t}$ as an example, the subscript $\{A, t\}$ represents the consumption good produced in sector A at period t, and the superscript i represents the good is finally consumed by consumer from sector i. Also $C_{A,t}$ represents the consumption goods produced in sector A at period t while consumed by consumer from sector A, and here the superscript A is omitted for notation simplicity.

2.2.1 Households

A representative household works at sector A and maximizes

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, N_t) \tag{2.1}$$

where N_t denotes the hours of labor, and C_t is a consumption bundle index defined by

$$C_t = \left[(C_{A,t})^{\frac{\eta-1}{\eta}} + (C_{B,t})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{2.2}$$

where η captures the substitution elasticity of goods consumption between sector A and other sectors, denoted as B. $C_{A,t}$ is an index of consumption of goods produced in sector A given by the constant elasticity of substitution function

$$C_{A,t} = \left(\int_0^1 C_{A,t}(j)^{1-\frac{1}{\epsilon}} dj\right)^{\frac{\epsilon}{\epsilon-1}}$$

where $j \in [0,1]$ denotes the good variety. Similarly, $C_{B,t}$ is an index of consumption of goods produced in other sectors $i \in [0,1], i \neq A$, given by

$$C_{B,t} \equiv \left(\int_0^1 (C_{i,t})^{1-\frac{1}{\gamma}} di\right)^{\frac{\gamma}{\gamma-1}}$$

where $C_{i,t}$ is an index of the quantity of goods consumed by household working in sector A and produced in sector i. By analogy, the consumption index $C_{i,t}$ is given by the same CES function as in the consumption index produced in sector A

$$C_{i,t} \equiv \left(\int_0^1 C_{i,t}(j)^{1-\frac{1}{\epsilon}} dj\right)^{\frac{\epsilon}{\epsilon-1}}$$

The maximization is subject to the the following budget constraint:

$$\int_0^1 P_{A,t}(j) C_{A,t}(j) dj + \int_0^1 \int_0^1 P_{i,t}(j) C_{i,t}(j) dj di + E_t\left[Q_{t,t+1} D_{t+1}\right] \leq D_t + W_t N_t + T_t \tag{2.3}$$

for $t = 1, 2, \cdots$ where $P_{A,t}(j)$ is the market price of good j produced at sector A, while $P_{i,t}(j)$ is the price of good j produced in sector i. Note that due to the Law of One Price, consumers from different sectors should be able to buy the same good with the same price, i.e., $P_{i,t}(j) = P^i_{i,t}(j)$, and $P_{A,t}(j) = P^i_{A,t}(j)$. Therefore, the superscripts of the price indices are omitted due to the LOOP. N_t denotes hours of work, W_t is the nominal wage, T_t denotes the lump-sum transfers/taxes, and D_{t+1} is the nominal payoff in period $t+1$ of portfolio held at the end of period t. $Q_{t,t+1}$ is the stochastic discount factor (SDF) between period t and $t+1$. Assume that households have access to a complete set of contingent claims, traded nationally.

Now the household must decide how to allocate its consumption expenditures among the differentiated goods produced within sector A, i.e., given the total expenditures spent on goods produced in sector A, the households maximize the consumption index $C_{A,t}$:

$$\begin{aligned} \max \quad C_{A,t} \qquad & s.t. \\ \int_0^1 P_{A,t}(j) C_{A,t}(j) dj & \equiv Z_{A,t} \end{aligned}$$

where we can write down the Lagrangian equation and derive the first order condition for every good produced in sector A, and thus obtain the demand equation for each firm j in sector A:

$$C_{A,t}(j) = \left(\frac{P_{A,t}(j)}{P_{A,t}}\right)^{-\varepsilon} C_{A,t}; C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_{i,t}}\right)^{-\varepsilon} C_{i,t} \tag{2.4}$$

where the second equality can be obtained similarly as the demand function for each firm j in sector i by households from sector A. $P_{A,t} = \left(\int_0^1 P_{A,t}(j)^{1-\varepsilon} dj\right)^{\frac{1}{1-\varepsilon}}$ is the sector

A's producer price index and $P_{i,t} = \left(\int_0^1 P_{i,t}(j)^{1-\varepsilon}dj\right)^{\frac{1}{1-\varepsilon}}$ is the sector i's price index. It can also be shown that $\int_0^1 P_{A,t}(j)C_{A,t}(j)dj = P_{A,t}C_{A,t}$ and $\int_0^1 P_{i,t}(j)C_{i,t}(j)dj = P_{i,t}C_{i,t}$.

Furthermore, the allocation of consumption for household in sector A among the goods produced in other sectors can be similarly decided:

$$C_{i,t} = \left(\frac{P_{i,t}}{P_{B,t}}\right)^{-\gamma} C_{B,t} \tag{2.5}$$

where $P_{B,t} \equiv \left(\int_0^1 P_{i,t}^{1-\gamma}di\right)^{\frac{1}{1-\gamma}}$ is the price index for all consumed goods produced in other sectors. Notice that $\int_0^1 C_{i,t}P_{i,t}di = C_{B,t}P_{B,t}$.

Finally, the optimal allocation of expenditures between goods produced in home sector or other sectors $C_{A,t}, C_{B,t}$ is decided by

$$\max C_t \quad w.r.t. \quad C_{A,t}, C_{B,t}$$

$$s.t. \quad P_{A,t}C_{A,t} + P_{B,t}C_{B,t} \equiv Z_t$$

By writing down the Lagrangian equation and the optimal allocation of expenditures between sectors is

$$C_{A,t} = \left(\frac{P_{A,t}}{P_t}\right)^{-\eta} C_t; C_{B,t} = \left(\frac{P_{B,t}}{P_t}\right)^{-\eta} C_t \tag{2.6}$$

where $P_t = [(P_{A,t})^{1-\eta} + (P_{B,t})^{1-\eta}]^{\frac{1}{1-\eta}}$ is the CPI. Accordingly, the period budget constraint can be rewritten as

$$P_t C_t + E_t \left[Q_{t,t+1} D_{t+1} \right] \leq D_t + W_t N_t + T_t \tag{2.7}$$

Moreover, assume the utility function has the form $U(C_t, N_t) = \frac{C_t^{1-\delta}}{1-\delta} - \frac{N_t^{1+\varphi}}{1+\varphi}$. Then the intra-temporal optimal condition is obtained from the trade-off between consumption and labor within the same period, i.e. the complete differential of C_t and N_t should satisfy both the objective function and the budget constraint:

$$C_t^{\sigma} N_t^{\varphi} = \frac{W_t}{P_t} \tag{2.8}$$

Meanwhile, the inter-temporal optimal condition can be derived from the trade-off of consumptions of period t and $t+1$:

$$\beta \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \left(\frac{P_t}{P_{t+1}} \right) = Q_{t,t+1} \tag{2.9}$$

Taking conditional expectation on both sides:

$$Q_t = \beta E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \left(\frac{P_t}{P_{t+1}} \right) \right] \tag{2.10}$$

where $Q_t \equiv E_t[Q_{t,t+1}]$denotes the price of a one-period discount bond paying off one unit of currency in $t+1$. The two optimal conditions can be respectively written in log-linearized form as

$$\begin{aligned} w_t - p_t &= \sigma c_t + \varphi n_t && (2.11) \\ c_t &= E_t\left(c_{t+1}\right) - \frac{1}{\sigma}\left(i_t - E_t(\pi_{t+1}) - \rho\right) && (2.12) \end{aligned}$$

Aside from the above optimal conditions from the consumer's decision making, one would like to know the relations between the identities mentioned above. Starting from the CPI and rewrite the formula:

$$P_t = \left[(P_{A,t})^{1-\eta} + (P_{B,t})^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

The log linearization can be done by approximating around the steady state where all price indices are constant: $P_t = P_{A,t} = P_{B,t} = P_0$. Suppose $p_t = log(P_t)$, $p_{A,t} = log(P_{A,t})$ and $p_{B,t} = log(P_{B,t})$,

$$\exp(p_t) = \left[(\exp\left(p_{A,t}\right))^{1-\eta} + (\exp\left(p_{B,t}\right))^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

The following relation holds:

$$p_t = \frac{1}{2}p_{A,t} + \frac{1}{2}p_{B,t} \qquad (2.13)$$

Assume $\pi_{A,t} = p_{A,t} - p_{A,t-1}$,$\pi_{B,t} = p_{B,t} - p_{B,t-1}$ and $\pi_t = p_t - p_{t-1} = \frac{1}{2}\pi_{A,t} + \frac{1}{2}\pi_{B,t}$.

Revisiting the inter-temporal condition for households of sector A:

$$\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\left(\frac{P_t}{P_{t+1}}\right) = Q_{t,t+1}$$

and by the symmetry of households from different sectors

$$\beta\left(\frac{C^i_{t+1}}{C^i_t}\right)^{-\sigma}\left(\frac{P^i_t}{P^i_{t+1}}\right) = Q_{t,t+1} \tag{2.14}$$

Without sector bias, we can derive the following relation between consumption:

$$C_t = C^B_t \tag{2.15}$$

2.2.2 Firms

Assume a typical firm from sector A produces a differentiated good represented by the production function (constant returns to scale)

$$Y_t(j) = A_t N_t(j)$$

where $j \in [0,1]$ is a firm-specific index.

We assume that firms from sector A set prices as follows. In each period, $1-\theta_A$ random selected firms will set new prices, while the rest of the firms do not adjust prices, with an individual firm's probability of re-optimizing in any given period being independent of the time elapsed since it last reset its price. Meanwhile, a fraction $1 - w_A$ of the firms, which we refer to as forward-looking firms, choose the price that maximizes the current market value of the profits generated while that price remains effective The remaining firms, of measure w_A, which we refer to as backward-looking, instead use a simple rule of thumb that is based on recent pricing behavior.

Suppose at period t and in sector A, if the firm is "randomly selected" to reset its price, a forward-looking firm will choose the price $P^f_{A,t}$, while the backward-looking firm will pick $P^b_{A,t}$. Let $S(t) \subset [0,1]$ represent the set of firms not re-optimizing the price in period t. $S_f(t) \subset S^c(t)$ represents the set of forward-looking firms who re-optimize its price in period t, and $S_b(t) \subset S^c(t)$ is the backward-looking firms re-optimizing the price in period t.

$$
\begin{aligned}
P_{A,t} &= \left[\int_0^1 P_{A,t}(j)^{1-\varepsilon} dj\right]^{\frac{1}{1-\varepsilon}} \\
&= \left[\int_{S(t)} P_{A,t-1}(j)^{1-\varepsilon} dj + \int_{S_f(t)} (P^f_{A,t})^{1-\varepsilon} dj + \int_{S_b(t)} (P^b_{A,t})^{1-\varepsilon} dj\right]^{\frac{1}{1-\varepsilon}} \\
&= \left[\theta_A \left(P_{A,t-1}\right)^{1-\varepsilon} + (1-\theta_A)(1-w_A)\left(P^f_{A,t}\right)^{1-\varepsilon} + (1-\theta_A) w_A \left(P^b_{A,t}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}
\end{aligned}
$$

And the log-linearization of the above formula around the steady state follows:

$$
p_{A,t} = \theta_A p_{A,t-1} + (1-\theta_A)\left[(1-w_A) p^f_{A,t} + w_A p^b_{A,t}\right] \tag{2.16}
$$

where the index for newly set prices can be expressed as $\bar{p}^*_{A,t} = (1 - w_A)\, p^f_{A,t} + w_A p^b_{A,t}$. And hence $p_{A,t} = \theta_A p_{A,t-1} + (1 - \theta_A)\, \bar{p}^*_{A,t}$.

$$\pi_{A,t} = p_{A,t} - p_{A,t-1} = (1 - \theta_A) \left(\bar{p}^*_{A,t} - p_{A,t-1} \right) \tag{2.17}$$

Therefore, sector inflation $\pi_{A,t}$ depends on the price index $\bar{p}^*_{A,t}$. To investigate the determinants of the prices, one should identify the price setting process of the two kinds of firms: forward-looking and backward-looking.

The optimal price-setting strategy for the typical forward-looking firm in sector A is identical to the firms in Calvo model:

$$\begin{aligned}
p^f_{A,t} &= (1 - \beta\theta_A) \sum_{k=0}^{\infty} (\beta\theta_A)^k\, E_t\, (\hat{mc}_{t+k} + p_{t+k}) \\
&= (1 - \beta\theta_A)\, (\hat{mc}_t + p_{A,t}) + (\beta\theta_A)\, E_t \left(p^f_{A,t+1} \right) \\
p^f_{A,t} - p_{A,t-1} &= (1 - \beta\theta_A)\, (\hat{mc}_t + \pi_{A,t}) + (\beta\theta_A)\, E_t \left(p^f_{A,t+1} - p_{A,t-1} \right) \\
&= (1 - \beta\theta_A)\, \hat{mc}_t + \pi_{A,t} + (\beta\theta_A)\, E_t \left(p^f_{A,t+1} - p_{A,t} \right)
\end{aligned}$$

where mc_{t+k} is the real marginal cost of firms from sector H at period $t + k$, and $\hat{mc}_{t+k}$ is the deviation from the steady state level mc.

Following Gali and Gertler(1999), the backward-looking firms obey a rule of thumb that has the following two features: (1) no persistent deviations between the rule and optimal behavior; i.e., in a steady state equilibrium the rule is consistent with optimal behavior; (2) the price in period t given by the rule depends only on information dated $t-1$ or earlier. These features lead us to a rule that is based on the recent pricing behavior of the firm's competitors

$$p^b_{A,t} = \bar{p}^*_{A,t-1} + \pi_{A,t-1} \tag{2.18}$$

And we have

$$p^b_{A,t} - p_{A,t-1} = \frac{\pi_{A,t-1}}{1-\theta_A} \tag{2.19}$$

Therefore, the sector inflation dynamics follows the following hybrid behavior:

$$\begin{aligned}
\left[1-(1-\theta_A)(1-\omega_A)+\beta\theta_A\omega_A\right]\pi_{A,t} &= (\beta\theta_A)\,E_t\left(\pi_{A,t+1}\right)+\omega_A\pi_{A,t-1} \\
&+ (1-\beta\theta_A)(1-\theta_A)(1-\omega_A)\,\hat{mc}_t
\end{aligned}$$

$$\pi_{A,t} = \gamma_f^A E_t\left(\pi_{A,t+1}\right) + \gamma_b^A \pi_{A,t-1} + \lambda^A \hat{mc}_t \tag{2.20}$$

2.2.3 Equilibrium

One the demand side, for sector A, the goods market clearing requires:

$$\begin{aligned}
Y_t(j) &= C_{A,t}(j) + C^B_{A,t}(j) && (2.21)\\
&= \left(\frac{P_{A,t}(j)}{P_{A,t}}\right)^{-\varepsilon}\left(\frac{P_{A,t}}{P_t}\right)^{-\eta} C_t && (2.22)
\end{aligned}$$

Plugging into the aggregate sector output $Y_t \equiv \left[\int_0^1 Y_t(j)^{1-\frac{1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}}$ yields

$$Y_t = \left(\frac{P_{A,t}}{P_t}\right)^{-\eta} C_t \tag{2.23}$$

Taking logs of both sides

$$y_t = c_t - \frac{\eta}{2}\left(p_{A,t} - p_{B,t}\right) \tag{2.24}$$

And similarly

$$y_t^B = c_t^B - \frac{\eta}{2}\left(p_{B,t} - p_{A,t}\right) = c_t - \frac{\eta}{2}\left(p_{B,t} - p_{A,t}\right)$$

The aggregate national output $y_t^* = y_t + y_t^B = c_t + c_t^B = 2c_t = c_t^*$.

On the supply side, the aggregate employment

$$N_t \equiv \int_0^1 N_t(j)dj = \frac{Y_t}{A_t}\int_0^1 \left(\frac{P_{A,t}(j)}{P_{A,t}}\right)^{-\varepsilon} dj \tag{2.25}$$

and up to a first-order approximation, $y_t = a_t + n_t$.

Next the real marginal cost

$$\begin{aligned} mc_t &= (w_t - p_{A,t}) - mpn_t \\ &= (w_t - p_{A,t}) - a_t \\ &= (w_t - p_t) + (p_t - p_{A,t}) - a_t \\ &= \sigma c_t + \varphi n_t + 1/2\,(p_{B,t} - p_{A,t}) - a_t \\ &= \frac{\sigma}{2} y_t^* + \varphi y_t - (1+\varphi)\,a_t + 1/2\,(p_{B,t} - p_{A,t}) \end{aligned}$$

Substituting the relation $1/2\,(p_{B,t} - p_{A,t}) = \frac{y_t - 1/2 y_t^*}{\eta}$ we are able to derive that the real marginal cost is determined by sector output as well as total output.

2.2.4 Comparisons and Implications to the Aggregate NKPC Model

The equilibrium in the goods market and the labor market, as well as the sector-specific hybrid pricing strategy support the following New Keynesian Phillips curve model:

$$\pi_{A,t} = c_A + \gamma_f^A E_t(\pi_{A,t+1}) + \gamma_b^A \pi_{A,t-1} + \alpha_1^A x_{A,t} + \alpha_2^A x_t + u_{A,t}$$

where inflation of sector A depends on sector specific inflation expectations, previous sector inflation, as well as economic slackness at sector level and aggregate level. In the recent work of Stock and Watson (2016), they regressed sector inflation on national unemployment gap in a sector-level Phillips curve and found that cyclical behavior varied substantially across sectors. Therefore, sector-varying coefficients are supported by theoretical model and empirical evidence. In the empirical part, I will be using unemployment gap as the measure for economic slack, and there are no unemployment gap variables available at sector level. For other measures of economic slackness such as the output gap variables, the aggregate and sector specific variables might be highly correlated with each other, and it makes identification of parameters even harder with potential endogeneity and multi-collinearity problems. Thus the sector NKPC considered from now on will focus on the relation between sector inflation and aggregate unemployment, and it seeks the main drivers of inflation dynamics in specific sectors with the general assumption across sectors that sector inflation is affected by sector specific inflation expectations, previous sector inflation, as well as current aggregate unemployment gap.

The sector A inflation dynamics can be extended to other sectors in the economy. Suppose the aggregate economy decomposes to N sectors. The producers from different sectors might have different pricing behavior. For example, the tradable goods prices change more frequently than the services prices. Meanwhile, the pricing behavior of firms from a specific sector can be affected by total employment status and the effect across sectors are allowed to vary. Therefore, in order to incorporate the pricing behavior across different sectors, the following separate regression on sector inflation dynamics are considered:

$$\pi_{it} = c_i + \gamma_f^{(i)} E_t \pi_{i,t+1} + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + u_{it} \tag{2.26}$$

where $i = 1, \cdots, N$ and $ugap_t$ represents the unemployment gap of the national economy at period t. A normalization of the parameters $\gamma_f^{(i)} + \gamma_b^{(i)} = 1$ holds in general, since the two coefficients tell us how the forward-looking and backward-looking pricing behavior are partitioned among firms in each sector. The current inflation rate in sector i depends on its own sector's future inflation expectation, previous sector inflation, as well as total unemployment gap. The parameters vary from sector to sector. Therefore, the estimates of this regression provide information on the determinants of sector inflation dynamics.

Moreover, besides the sector specific inflation dynamics, the total inflation rate can be measured by the weighted value of sectoral inflation rates, and thus predicted by averaging up each separate regression. By adding up the weighted average of sector inflation dynamics on both sides, a closed-form implied aggregate NKPC model may not be derived in the same form as the implied national model from regional variation (see chapter 1) due to the sector specific parameters in the regression. Instead, the aggregate inflation is derived to be affected by disaggregate inflation rates directly:

$$\begin{aligned}
\sum_{i=1}^{N} \omega_i \pi_{it} &= \sum_{i=1}^{N} \omega_i c_i + \sum_{i=1}^{N} \omega_i \gamma_f^{(i)} E_t \pi_{i,t+1} + \sum_{i=1}^{N} \omega_i \gamma_b^{(i)} \pi_{i,t-1} + \sum_{i=1}^{N} \omega_i \beta^{(i)} ugap_t + \sum_{i=1}^{N} \omega_i u_{it} \\
\pi_t &= c + \sum_{i=1}^{N} \omega_i \gamma_f^{(i)} E_t \pi_{i,t+1} + \sum_{i=1}^{N} \omega_i \gamma_b^{(i)} \pi_{i,t-1} + (\sum_{i=1}^{N} \omega_i \beta^{(i)}) ugap_t + u_t
\end{aligned}$$

where $\pi_t = \sum_{i=1}^{N} \omega_i \pi_{it}$ is the weighted average of inflation rates across sectors. After taking aggregation, the aggregate inflation is affected by disaggregate information and the weighted regression cannot be directly reduced to the form of pure aggregate information due to the sector-varying coefficients. However, one can still make implications to the aggregate inflation dynamics based on the sector inflation dynamics, and these results can be compared to the implications made from the aggregate NKPC directly estimated using aggregate data:

$$\pi_t = c + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \beta ugap_t + u_t$$

Although the weighted sector inflation dynamics is not directly comparable with the aggregate inflation dynamics, comparisons of related parameters in these two models can still be informative. For instance, if one expect there would be a 1% increase in the inflation expectations in all sectors, then the expectation for the aggregate inflation will also increase by 1%. Implied by the estimators of the sector NKPC model, this will cause the current total inflation rate to increase by $(\sum_{i=1}^{N} w_i \gamma_f^{(i)})$%. While the aggregate NKPC model suggests the increase in current inflation rate will be π_f%. Implications on inflation dynamics can be made by comparing the estimation of these two parameters. Meanwhile, notice that the slackness measurement $ugap_t$ is invariant across sectors, and one can measure the pressure of national slackness on total inflation rate by adding up sectoral estimates $\sum_{i=1}^{N} w_i \beta^{(i)}$ and compare to the aggregate estimate β.

2.2.5 Econometric Approach

Nevertheless, the sector NKPC model has to deal with the endogeneity problem. The sector inflation expectations are unobservable, and at the same time, the unemployment gap rates are potentially endogenous. There might be cost push shocks that can both affect prices as well as employment decisions. The proxies used to measure the expectation terms are the corresponding realized sector inflation rates, as being used a lot in the literature (see [35], [36], [20], and [14]). For each sector, one can write down the following regressions:

$$\pi_{it} = c_i + \gamma_f^{(i)} \pi_{i,t+1} + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + \tilde{u}_{it}$$

where $\tilde{u}_{it} = u_{it} + \gamma_f^{(i)}(\pi^e_{i,t+1} - \pi_{i,t+1})$. The potentially endogenous variables in each separate regression are $\pi_{i,t+1}$ and $ugap_t$. The identification strategy is that for any sector i, the error term u_{it} does not depend on any previous information, on both aggregate level and disaggregate level, $E_{t-1}(u_{it}) = 0$. Therefore, the parameters in each regression can be identified and thus estimated by the linear GMM method.

Lagged variables are considered as both valid instruments and relevant instruments due to the identification assumption imposed above and persistence in macroeconomic variables. Originally if we consider p time series as potential instruments, the instrument vector Z_{it} will use up to M lags of these p series, and thus we construct the unconditional moments $E(\tilde{u}_{it}Z_{it}) = 0$. As a result, the instrument set Z_{it} contains Mp instruments in total. There might exist an infinite number of predetermined variables as potential instruments. However, too many instruments will cause weak instruments issues and result in biased estimates in finite samples. Meanwhile, the choice of lag M is arbitrary and M can be as large as the sample period T. Consequently, a careful choice of M and effective instrument selection procedure are crucial for precise estimation. In the following estimation, I choose M following the line of [22].

Within each sector NKPC, potential instruments include lagged aggregate and disaggregate sectoral inflation rates, consumption expenditure growth rates as well as previous unemployment gap. In the following empirical part, Lasso and kernel-weighted Lasso procedures are applied in separate sector regressions for instrument selection. As was discussed in the first chapter, Lasso and kernel-weighted Lasso methods manage to shrink the coefficients of unimportant instruments to zero in the first stage regression, while the latter also deals with the assumption that more recent instruments contain more information than more distant ones. After the instruments are selected using specific approaches, the selected instruments are used directly to form the unconditional moments for GMM estimation, as the post-Lasso estimation method in [10].

In the first chapter, there are simulation studies showing that GMM estimates with selected instruments from kernel-weighted Lasso outperform the estimates using instruments selected by Lasso or no selection, both in national and regional level. For each sector, the sector regression is similar to the national regression and thus we believe that GMM estimates using kernel-weighted Lasso selected instruments should be more plausible than the alternative approaches. Therefore, in the empirical part, I will discuss the comparisons between estimates and focus on the improvement in the estimation from using kernel-weighted Lasso to select instruments and the benefits to the estimation through considering sector variation.

2.3 Empirical Results

This section discusses the sector specific estimation results as well as implied aggregate coefficients. The GMM estimators with different instrument selection procedures are provided and compared. Furthermore, a comparison between the implied aggregate results from sector estimates and the direct aggregate results will be made, along with further discussions on cyclical behavior of sectoral inflation.

2.3.1 Data

The data set consists of observations on thirteen components of inflation used to construct the core PCE price index from NIPA tables 2.3.4 and 2.3.5, including 4 durable goods, 2 nondurable goods, and 7 service sectors. The raw data in the sample are quarterly observations from 1980Q1 to 2016Q4. Throughout, inflation is measured in percentage points at an annual rate.

The unemployment gap variable is calculated by subtracting NAIRU (available from Congressional Budget Office) from the quarterly unemployment rates downloaded from Bureau of Labor Statistics. Lagged personal consumption expenditures by sector downloaded from NIPA table 2.3.5 are also used as potential instruments.

Import penetration or exposure data are also considered to link to the various cyclical behavior across sectors. The variables I refer to are the changes of upstream and downstream import exposure by industry publicly available from David Dorn's website. I aggregate the more disaggregated industry components to sub-sectors in order to match with the core personal consumption expenditure sectors.

2.3.2 Results

Table 8 shows the estimates of the forward-looking parameter γ_f and economic slackness pressure (Phillips coefficient) β in the aggregate model as well as the sector-implied aggregate model. As discussed, the series of previous periods can be treated as relevant and valid instruments due to the persistent effects of macro-economic variables and the independence between innovations and past information. With 148 quarterly observations from 1980 to 2016, I use up to 5 lags of core and sectoral inflation rates, personal consumption expenditure and national unemployment gap rates. In total, 145 instruments are used in the original instrument set. I calculate the share weight of each sector based on the consumption expenditure and assume it is constant over the selected period. Three categories of estimates are compared: the GMM estimates with all instruments and with optimal instruments formed by Lasso and kernel-weighted Lasso respectively.

There are several interesting findings. First, in both aggregate and sectoral estimates, selected instruments suggest a more forward-looking behavior of firms. For example, in the implied aggregate estimation results ($\sum_{i=1}^{N} w_i \gamma_f^{(i)}$), estimates using all instruments suggest that roughly 57.4% of inflation is driven by future expectations, while the estimation using kernel-weighted Lasso selected instruments shows that the aggregate inflation is around 64.8% driven by expectations.

Second, the implied aggregate model estimates derived from the sector model show a significant negative relation between inflation and unemployment gap. If we only focus on aggregate data, the aggregate estimates fail to show the significantly negative relationship even after selecting the instruments with kernel-weighted Lasso. The Phillips curve has been extensively discussed in recent papers and in the speeches of policy makers ([8], [2], [17]). It is accepted that the relation has become flatter and insignificant. One possible reason might be the time-varying coefficients from the aggregate New Keynesian Phillips curve, in which case there are only 148 quarterly observations available. Similar reasons have been discussed in the first chapter, and the introduction of disaggregated sector data could contribute to more precise parameter estimates by enlarging the data set and thus reducing the standard errors of the corresponding estimates. More specifically, in the sector model, we have both sector specific variables as well as aggregate variables considered in the regression. From the results, it is noticeable that the standard errors of the weighted coefficients $\sum_{i=1}^{N} \omega_i \gamma_f^{(i)}$ and $\sum_{i=1}^{N} \omega_i \beta^{(i)}$ are much smaller than their aggregate counterparts γ_f and β. The calculation of these standard errors needs to take cross-sector and cross-period correlation of moments into consideration. The covariances of cross-sector coefficients are obtained by computing the weighted sum of the covariances of moment conditions, where the weight factor is similarly defined as in Newey-West HAC estimator. Detailed construction procedures are shown in the appendix.

In order to take a closer look at how firms from different sectors are affected by real economic activity, table 9 and table 10 show the estimation results of each sector. Table 9 shows the sector estimation results of γ_f obtained via the kernel-weighted Lasso approach. We consider 13 types of goods and services produced in different sectors and consumed by private consumers. Sectors 1 to 4 are considered as durable goods, sector 5 and 6 are nondurable goods, while the rest of them are referring to the services sector. As shown in table 8, the implied aggregate inflation is more forward-looking after instruments are selected by kernel-weighted Lasso, and this increase is contributed by each separate sector regression. If we compare firms' forward-looking behavior across the two larger categories: goods and services, table 9 suggests that firms in service sectors are more forward-looking compared to other firms in goods sectors. To a large extent, the forward-looking behavior of a firm's pricing strategy is affected by the price rigidity in the sector. And the estimation results show that on average, firms in goods sector adjust prices more frequently than firms in service sectors.

Table 10 presents the estimation of β for each sector. Unfortunately, most of these β's are insignificant due to lack of observations and time-varying coefficients, for similar reasons to the aggregate estimation. However, these estimates are still informative for us to discuss how real economic factors affect firms across sectors differently. While goods prices are more driven by short-term price adjustment and import prices, sector prices depend on forward-looking expectations as well as slackness in the labor market. For example, the β estimate for health care services sector is significantly negative, while the estimates in most goods sectors, especially durable goods sectors, are insignificant and even with the wrong sign.

The insignificance might arise from international competition that when goods are trade-able across nations, specific inflation dynamics might rely less on local labor market. Table 11 provides a comparison of β estimates and import penetration index for selected sectors. Since there is no exact one-to-one mapping between industry code and PCE sectors, here I compare eight selected sectors: four from durable goods sector, two from nondurable goods sector and two from services sector. Import penetration index (IPI for short in table) is a scaled measure of changes in import of a specific sector. A higher downstream import exposure means there exists more competition for the sector from imports. On average, the import penetration index is highest for durable goods sectors while lowest for services sectors, since firms from durable goods sectors might face more international competition than those from services sectors. Instead, firms from services sectors may rely more on local labor market conditions. Table 11 shows the link between β estimates and import penetration index. Even though most estimates of β are not significant, we can still find that the Phillips coefficients of services sectors are more significant than those of goods sectors.

2.3.3 Extension: Structural Break

As was discussed in earlier sections, the Phillips curve has become “flatter” recently, and time-varying Phillips coefficients is a potential reason that causes insignificance in the recent national estimates. Therefore, it is also interesting to check whether there exist structural breaks within the sample, and if so, whether we can obtain any implications by running separate regressions on split subsamples.

In the literature, there have been empirical evidence showing that the slope of the Phillips curve has been flatter since the early 2000s [1]. And in this section, I divide the original sample into two subsamples, with the first quarter of 2000 being the starting period of the second subsample. The sector specific regression and aggregate regression will be estimated based on the two subsamples, with instruments selected using the proposed sparse methods. Direct aggregate and implied aggregate estimation results can be compared across samples to see if there exist structural breaks in the Phillips curve during the selected sample period.

Tables 12 and 13 show the empirical aggregate and implied aggregate empirical estimation of forward-looking behavior (the γ_f's) and Phillips coefficient (the β's) based on the two subsamples. We can draw similar conclusions about the improvement from the implied aggregate estimates using selected instruments on both subsamples as on the whole sample. If we compare the results across samples, the implied aggregate results with kernel-weighted Lasso suggest that after 2000, firms are more forward-looking and it might arise from a focus of expectation management used as monetary policy tools to stabilize inflation in recent years. According to the implied aggregate inflation dynamics, a 1% increase in inflation expectations will contribute to around 0.6 percent increase in aggregate inflation, while after 2000, the change in inflation will increase to around 0.78 percent. Other than the changes of the parameter on forward-looking inflation behavior, there also exists evidence on the slope changes during the period: after 2000, economic slackness imposes a lower pressure on the pricing behavior compared to the impact before 2000. Table 12 shows that before 2000, relation between inflation and unemployment gap is significantly negative and relatively high (around -0.067), while in table 13, the corresponding coefficient ($\sum_{i=1}^{N} \omega_i \beta^{(i)}$) decreases to -0.0143 and becomes insignificant. One possible reason for the insignificance might result from lack of observations after 2000. It might also be the result of international competition and globalization which leads to a flatter Phillips curve.

2.4 Conclusion

This paper examines the potential for a better understanding the aggregate inflation dynamics, by considering disaggregated sector level data, as well as selected instruments. Instead of regressing regional data in a pooled regression in the first chapter, I derive sector specific NKPC by incorporating divergent pricing behavior of firms across sectors. Within each sector, there exists a large set of potential instruments: lagged sector variables and aggregate variables. The first chapter shows that the GMM estimators with instruments selected by kernel weighted Lasso approach performs the best in finite samples with instruments of lag structure. Therefore, the instrument selection method is carried over from the first chapter and applied to estimate the sector specific regressions.

As sector variation is introduced and sector specific inflation dynamics are studied, we get to know the sector inflation dynamics from the estimates of each sector model. Furthermore, the sector model estimates can not only show the sector inflation dynamics, but also imply a more efficient aggregate estimate. In the empirical work, I show that both sector and aggregate inflation dynamics are more forward-looking that would be estimated without instrument selection. Meanwhile, there still exists a negative relation between sector inflation and aggregate labor market slackness for most sectors. The relation becomes more significant when it comes to services sectors instead of goods sectors. In addition, the relation between aggregate inflation and unemployment is significantly negative if the sector inflation dynamics are averaged up to aggregate dynamics.

Table 2.1: Empirical Results: Comparison of Aggregate and Disaggregate Estimates

	All Instruments		Lasso		Kernel-weighted Lasso	
	estimates	S.E.	estimates	S.E.	estimates	S.E.
γ_f	N.A.	N.A.	0.6005	0.0378	0.6911	0.0631
$\sum_{i=1}^{N} w_i \gamma_f^{(i)}$	0.574	0.0099	0.6190	0.0102	0.6478	0.0116
β	-0.0089	0.0956	0.0091	0.0303	-0.0306	0.0344
$\sum_{i=1}^{N} w_i \beta^{(i)}$	-0.0395	0.0258	-0.0057	0.0072	-0.0207	0.0092

Notes: Based on quarterly US sector data in the period 1980-2016. This table reports the estimation of the US NKPC parameters using aggregate data only in the aggregate model: $\pi_t = c + \gamma_f E_t(\pi_{t+1}) + (1-\gamma_f)\pi_{t-1} + \beta ugap_t + u_t$, as well as the weighted parameters obtained by estimating the sector NKPC : $\pi_{it} = c_i + \gamma_f^i E_t(\pi_{i,t+1}) + \gamma_b^i \pi_{i,t-1} + \beta^i ugap_t + u_{it}$. Correspondingly, the standard errors are also reported.

Table 2.2: Sector Results of γ_f: kernel-weighted Lasso approach

Sector Name	estimates	S.E.	t-statistic
1. Motor Vehicles and Parts	0.677	0.026	26.388
2. Furnishings and durable household equipment	0.680	0.043	15.959
3. Recreational goods and services	0.490	0.039	12.581
4. Other durable goods	0.543	0.032	17.030
5. Clothing and footwear	0.761	0.035	21.930
6. Other nondurable goods	0.673	0.033	20.341
7. Housing and utilities	0.611	0.026	23.820
8. Health care	0.570	0.040	14.122
9. Transportation services	0.683	0.030	22.970
10. Recreation services	0.697	0.032	21.701
11. Financial services and insurance	0.651	0.049	13.385
12. Other services	0.780	0.041	19.122
13. Final consumption expenditures of nonprofit institutions	0.710	0.042	17.066

Notes: Based on quarterly US sector data in the period 1980-2016. This table reports the GMM estimates of γ_f with Kernel-weighted Lasso selected instruments of the sector model: $\pi_{it} = c_i + \gamma_f^{(i)} E_t(\pi_{i,t+1}) + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + u_{it}$ as well as the corresponding standard errors and t statistic for each sector.

Table 2.3: Sector Results of β: kernel-weighted Lasso approach

Sector Name	estimates	S.E.	t-statistic
1. Motor Vehicles and Parts	-0.019	0.050	-0.373
2. Furnishings and durable household equipment	0.023	0.043	0.528
3. Recreational goods and services	-0.053	0.031	-1.677
4. Other durable goods	0.006	0.048	0.125
5. Clothing and footwear	-0.079	0.056	-1.397
6. Other nondurable goods	-0.054	0.036	-1.519
7. Housing and utilities	-0.018	0.016	-1.139
8. Health care	-0.044	0.016	-2.711
9. Transportation services	0.013	0.041	0.313
10. Recreation services	-0.040	0.032	-1.238
11. Financial services and insurance	0.004	0.022	0.192
12. Other services	0.017	0.023	0.722
13. Final consumption expenditures of nonprofit institutions	0.040	0.068	0.586

Notes: Based on quarterly US sector data in the period 1980-2016. This table reports the GMM estimates of β with Kernel-weighted Lasso selected instruments of the sector model: $\pi_{it} = c_i + \gamma_f^{(i)} E_t(\pi_{i,t+1}) + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + u_{it}$ as well as the corresponding standard errors and t statistic for each sector.

Table 2.4: Import Penetration Index (IPI) and Sector Specific β Estimates

Sector Name	IPI	estimates	S.E.	t-statistic
1. Motor Vehicles and Parts	$1.06 \sim 6.02$	-0.019	0.050	-0.373
2. Furnishings and durable household equipment	$0 \sim 3.85$	0.023	0.043	0.528
3. Recreational goods and services	$0 \sim 10.75$	-0.053	0.031	-1.677
4. Other durable goods	$0.15 \sim 4.59$	0.006	0.048	0.125
5. Clothing and footwear	$0.59 \sim 3.71$	-0.079	0.056	-1.397
6. Other nondurable goods	$0.11 \sim 2.91$	-0.054	0.036	-1.519
8. Health care	$0.28 \sim 1.28$	-0.044	0.016	-2.711
10. Recreation services	$0.26 \sim 0.98$	-0.040	0.032	-1.238

Notes: This table links the GMM estimates of β using KLasso selected instruments with the import penetration index of each sector. Notice that higher index corresponds with more significant relation between sector inflation and economic slackness.

Table 2.5: Empirical Results: Split Sample 1980Q1-1999Q4

	All Instruments		Lasso		Kernel-weighted Lasso	
	estimates	S.E.	estimates	S.E.	estimates	S.E.
γ_f	0.5579	0.0802	0.4649	0.0933	0.6073	0.1329
$\sum_{i=1}^{N} w_i\gamma_f^{(i)}$	0.5148	0.0468	0.5032	0.0252	0.5913	0.0352
β	0.0481	0.0579	-0.0238	0.0912	-0.0564	0.0559
$\sum_{i=1}^{N} w_i\beta^{(i)}$	-0.0401	0.0471	-0.0234	0.03	-0.067	0.0334

Notes: Based on quarterly US sector data in the period 1980-1999. This table reports the estimation of the US NKPC parameters using aggregate data only in the aggregate model: $\pi_t = c + \gamma_f E_t(\pi_{t+1}) + (1-\gamma_f)\pi_{t-1} + \beta ugap_t + u_t$, as well as the weighted parameters obtained by estimating the sector NKPC : $\pi_{it} = c_i + \gamma_f^i E_t(\pi_{i,t+1}) + \gamma_b^i \pi_{i,t-1} + \beta^i ugap_t + u_{it}$ on the first half of the sample. Correspondingly, the standard errors are also reported.

Table 2.6: Empirical Results: Split Sample 2000Q1-2016Q4

	All Instruments		Lasso		Kernel-weighted Lasso	
	estimates	S.E.	estimates	S.E.	estimates	S.E.
γ_f	0.4966	0.1005	0.5255	0.0439	0.6618	0.1012
$\sum_{i=1}^{N} w_i \gamma_f^{(i)}$	0.4267	0.0789	0.5566	0.0268	0.7858	0.044
β	0.0175	0.0298	0.018	0.0224	-0.0078	0.0261
$\sum_{i=1}^{N} w_i \beta^{(i)}$	0.0487	0.0928	0.0058	0.0211	-0.0143	0.023

Notes: Based on quarterly US sector data in the period 2000-2016. This table reports the estimation of the US NKPC parameters using aggregate data only in the aggregate model: $\pi_t = c + \gamma_f E_t(\pi_{t+1}) + (1 - \gamma_f)\pi_{t-1} + \beta ugap_t + u_t$, as well as the weighted parameters obtained by estimating the sector NKPC : $\pi_{it} = c_i + \gamma_f^i E_t(\pi_{i,t+1}) + \gamma_b^i \pi_{i,t-1} + \beta^i ugap_t + u_{it}$ on the second half of the sample. Correspondingly, the standard errors are also reported.

Chapter 3

Inflation Dynamics in the Euro Area

3.1 Introduction

Since 1999, the member states of the euro area have transferred their power of monetary policy to the European central bank (ECB). [37] pointed out that the official stance of the ECB has been that policy decisions are reflective of changing economic conditions of the euro area as a whole rather than its individual constituent countries. The effectiveness of this "one size fits all" monetary policy has faced criticism from many aspects, and the relationship between member states and the euro area is different from that between the regions and the United States. In US, regional imbalances tend to be more mean-reverting, owing to higher levels of labor mobility and more flexible product and labor market [38]. While the first chapter considers a pooled regression for regional inflation dynamics in the US, for the analysis of inflation dynamics of euro area in this paper, cross-country heterogeneity needs to be taken care of in order to gauge the effectiveness of the joint monetary policy. After the recent crisis, not only in the US, but also in other advanced economies, such as the euro area, we observe missing disinflation with respect to a considerable level of slackness if predicted using a Phillips curve estimated before the crisis. This chapter looks at the inflation dynamics in the euro area by considering cross-country heterogeneity and more importantly, it seeks the potentials to improve the estimation of aggregate inflation dynamics in this area by incorporating disaggregate level data.

A growing body of literature has compared the performance of a single monetary policy for all euro area members relative to other alternatives (see [39]; [40]; [41]). Notably, [42], [43] and [44] compare the performance of a monetary policy rule based on aggregate euro area data as a whole against an alternative policy rule that relies on national data by taking into account country-specific idiosyncrasies. [45] discuss two potential reasons of remarkably stable inflation since the Great Recession even though unemployment has increased significantly: more anchored inflation expectations due to increased central banks' independence, and a flatter Phillips curve relationship. One monthly bulletin of [46] argues that the evolution of Phillips curve and its implications for future inflation in the euro area rely on choices of specifications, the slackness measure used in the Phillips curve and cross-country heterogeneity. Meanwhile, the short history of the central bank has hampered earlier empirical work on the euro area monetary policy, with potential structural breaks within the available sample period. The limitations and uncertainties in the Phillips curve suggest a comprehensive consideration of disaggregate information.

The reason to consider instrument selection is to reduce finite sample bias in each separate regression, similar to that in the national, regional and sectoral cases (see [4]; [5];[6];[7]). There are two main reasons for considering disaggregated national information in the euro area in order to further improve the estimation of total inflation dynamics. First, national inflation dynamics are often driven by different processes, due to country heterogeneity in economic structure. In order to assess real economic and price developments, it is also interesting and important to pay attention to separate national inflation dynamics. The results of the existing literature not only indicate that variables can have markedly different explanatory power for price movements of different countries, but also suggest that the variables may become less informative when used directly to explain movements in inflation at the aggregate level. Second, the introduction of national information improves the estimation efficiency of aggregate inflation dynamics by enlarging the data set and reducing the standard errors of implied aggregate inflation dynamics coefficients. Thus the estimation of aggregate inflation dynamics can be further improved by averaging separate disaggregate national regressions.

This paper contributes to improving the estimation of aggregate inflation dynamics in the following aspects. First, I show in a conceptual model that there are various specifications of the Phillips curve across countries. This phenomenon is particularly relevant in the euro area, whose constituent countries display substantial heterogeneity in economic structure and institutional landscape, especially relating to labor and product market. On average, firms located in different countries are allowed to have various speeds of price adjustment and pricing strategies, and thus national NKPC is defined to demonstrate specific inflation dynamics for each country. To obtain national inflation dynamics, we need to estimate separate regressions, which may encounter many instrument issues with lagged variables used as instruments. This is a similar case to the inflation dynamics of national, regional or sector level discussed in the first and second chapters, and the kernel-weighted Lasso method is applied to select instruments with lag structure and reduce finite sample estimation bias.

Second, I show that aggregate inflation dynamics can be estimated more precisely and efficiently by a taking weighted average of each separate national inflation dynamics. The previous estimates using aggregate information have shown insignificant estimates of the Phillips curve slope, no matter what instrument selection method is applied. However, if the aggregate inflation dynamics are estimated and inferred using national data in separate models, this paper shows that there exists a statistically significant trade-off between inflation and unemployment on average.

Last but not least, I also pay attention to the individual estimates of national inflation dynamics. Country heterogeneity in labor or product market in the euro area has been shown in the separate estimates. All the member states in the euro area can be divided into different categories according to the national specific estimates. It is also interesting to discuss why some countries still show a strong trade-off between inflation and unemployment even with the onset of financial crisis, while others become insignificant. These heterogeneous patterns of national inflation dynamics are informative to understand the aggregate economic developments.

This chapter proceeds as follows. Section 2 discusses the New Keynesian Phillips curve for each country and for the euro area with a continuum of small countries. Each separate national model allows for different price rigidities and different proportions of backward-looking firms across countries. National inflation and implied aggregate inflation dynamics are estimated and compared to the aggregate inflation dynamics. The estimation of each disaggregate NKPC and also the aggregate NKPC needs to deal with many instruments issues since many lagged variables are considered as potential instruments. Lasso and kernel-weighted Lasso techniques are applied to select instruments. Section 4 explores the empirical study with the euro area data. Implied aggregate inflation dynamics as well as separate inflation dynamics will be estimated and discussed, and a full conclusion is presented in section 5.

3.2 A Conceptual Model

In this section, I will describe a conceptual model of the NKPC for each nation within the euro area following the line of [15], which will be used in separate national regressions and can imply aggregate results. Suppose the euro area economy is modeled with a continuum of small nations, represented by the unit interval $[0, 1]$. Different countries are subject to imperfectly correlated productivity shocks. Each country has a representative household and a continuum of firms producing a differentiated good, also represented by the unit interval. Compared to the rest of the euro area economy, the performance of each nation does not have an impact on the whole euro area. Also, each country is assumed to share identical consumer preferences, but meanwhile, to display substantial heterogeneity in economic structure and institutional landscape. The relations of the macroeconomic variables and the agents' behavior are discussed in the home country H and compared to all the other foreign countries F. The country index F represents a general notation for all other foreign countries $i \in [0, 1]$ other than home country.

3.2.1 Households and Firms

From the demand side, the consumer's problem is similar to the problems we have discussed in the regional and sectoral NKPC models in previous chapters. The optimal consumption allocation for each good produced by either domestic or foreign firms depends on the relative prices as well as the substitution elasticities of goods. Also, national CPI is a weighted average of domestic produced goods price index and foreign produced goods price index, with the weight being defined as home bias parameter. Therefore, roughly speaking, national CPI inflation dynamics depends on both domestic and foreign firms' pricing decisions, and the parameters in each country's inflation dynamics should be allowed to vary across countries due to firms' asymmetric pricing behavior.

From the perspective of the supply side, we assume that firms' pricing behavior in each country display heterogeneous impact coefficients magnitudes. Empirical evidence shows that countries in the euro area focus on producing different types of goods or services as a result of comparative advantage and trade specialization. For example, there are countries specializing in industry and manufacturing, like Germany and Ireland in the euro area, while other countries might have comparative advantages on wholesale, transportation or service sector. Each industry has its own price adjustment speed, and the difference on average will cause the firms of one country have different price adjustment speeds from firms of another country, due to the country's specialization. Then, for home country H, domestic firms can update prices with a country-specific probability $1-\theta_H$, and during one period, a fraction $1-\omega_H$ of all the firms that are updating their prices choose the price that maximizes the current market value of the profits generated while that price remains effective. The remaining firms, of measure ω_H and referred to as backward-looking firms, use a rule of thumb that is based on recent domestic and foreign pricing behavior.

By solving the pricing decisions of both forward-looking and backward-looking types of firms, as well as the equilibrium in the goods market and the labor market, the country-specific hybrid pricing strategy support the following New Keynesian Phillips curve model for the country i:

$$\pi_{it} = c_i + \gamma_{f1}^i E_t(\pi_{i,t+1}) + \gamma_{b1}^i \pi_{i,t-1} + \gamma_{b2}^i \pi_{t-1} + \alpha_1^i x_{it} + u_{it} \tag{3.1}$$

where inflation of country i ($\pi_{i,t}$) depends on: (1) national inflation expectations $E_t(\pi_{i,t+1})$, (2) previous national inflation $\pi_{i,t-1}$, (3) previous euro area inflation π_{t-1} and (4) national unemployment rate x_{it}. Suppose the total inflation rate in the euro area is decomposed to N countries, and $i = 1, 2, \cdots, N$. The euro area aggregate inflation rate π_t is a weighted average of inflation rates across countries at period t: $\pi_t = \sum_{i=1}^N \omega_i \pi_{it}$, $\sum_{i=1}^N \omega_i = 1$. Parameters with subscript 1 refer to the impacts of national specific determinants on national inflation, while parameters with subscript 2 refer to the impacts of area or global determinants on national inflation dynamics. In the equation above, α_1 is a parameter referred to as the slope of the country specific Phillips curve. We introduce both rational expectations of inflation and lagged inflation to allow for forward-looking behavior of firms and some inflation persistence. The parameters γ_{f1}^i and γ_{b1}^i capture the proportions of national factors. Meanwhile, γ_{b2}^i represents the effect of area inflation persistence on current domestic inflation rates and this coefficient incorporates the contention that globalization makes inflation dependent on global or area factors. For instance, import prices changes can have effect on national inflation rates. A normalization of the parameters $\gamma^i_{f1} + \gamma^i_{b1} + \gamma^i_{b2} = 1$ holds in general, and these coefficients tell us how the forward-looking and backward-looking pricing behavior are partitioned among firms in each country, and how national specific inflation relies on national factors as well as area-wide factors. The parameters vary from country to country. The regression equation also allows for transitory national shocks u_{it}, which captures fluctuations in national inflation that may be driven by temporary country-specific supply factors.

We can also consider euro area inflation expectations ($E_t(\pi_{t+1})$) and total unemployment rates (x_t) as potential determinants of national inflation dynamics in the regression above. These two variables are not used in this paper here for the following reasons. First, the aggregate inflation expectations are highly correlated with the national inflation expectations, and both of them are not directly observed in the data and potentially endogenous. It might cause some identification issues to estimate the regression with both expectation terms. Second, the euro area is a monetary union within which the members use the same currency and are affected by the joint monetary policy. However, the countries still have their own independence in other aspects of the economy, such as different fiscal policies and different status of economic reforms. The labor markets across countries in the euro area are relatively less mobile than those local labor markets in the US. Hence the firms' pricing behavior are more related to the local labor market condition than they are related to the area-wide labor market. For these two reasons, I exclude the two aggregate level variables from the national regression.

[47] argues that the estimation of inflation dynamics in the euro area might be improved by increasing the length of sample period or the level of disaggregation. The relationship between inflation and unemployment are changing over time, especially after the recent crisis, there might exist structural changes in the Phillips curve relation. The euro area data only exists after 2000, with possible structural changes in the dataset, researchers argue that forecasting the euro area inflation may suffer from estimation errors. In order to improve the estimation precision and the forecasting performance of the euro area inflation, it helps to consider more disaggregated data to increase the sample size and thus reduce the estimation error. Therefore, country-specific NKPC model and coefficients are reasonable concerns when estimating the inflation dynamics in the euro area. By studying the separate regression on each country, one can learn not only the national inflation dynamics for each country within the euro area, including the mixed pricing behavior of the firms, but also the structural relationship between inflation and unemployment at national level. Moreover, the total inflation rate can be measured by the weighted value of national inflation rates, and thus predicted by averaging up each separate regression.

3.2.2 Comparisons and Implications to the Euro Area NKPC Model

Since the total average inflation rate in the euro area is the weighted average of national inflation rates, several important implications on national inflation dynamics can be revealed. By adding up the weighted average of national inflation dynamics on both sides, a closed-form implied overall NKPC model may not be derived as the implied euro area model from national variation, instead, the total inflation is affected by disaggregated inflation to different degrees.

$$\begin{aligned}
\sum_{i=1}^{N}\omega_i\pi_{it} &= \sum_{i=1}^{N}\omega_i c_i + \sum_{i=1}^{N}\omega_i\gamma_{f1}^{i}E_t(\pi_{i,t+1}) + \sum_{i=1}^{N}\omega_i\gamma_{b1}^{i}\pi_{i,t-1} \\
&\quad + \sum_{i=1}^{N}\omega_i\gamma_{b2}^{i}\pi_{t-1} + \sum_{i=1}^{N}\omega_i\alpha_1^{i}x_{it} + \sum_{i=1}^{N}\omega_i u_{it} \\
\pi_t &= c + \sum_{i=1}^{N}\omega_i\gamma_{f1}^{i}E_t(\pi_{i,t+1}) + \sum_{i=1}^{N}\omega_i\gamma_{b1}^{i}\pi_{i,t-1} \\
&\quad + \sum_{i=1}^{N}\omega_i\gamma_{b2}^{i}\pi_{t-1} + \sum_{i=1}^{N}\omega_i\alpha_1^{i}x_{it} + \sum_{i=1}^{N}\omega_i u_{it}
\end{aligned}$$

where $\pi_t = \sum_{i=1}^{N}\omega_i\pi_{it}$ as already defined above. Since the coefficients vary across countries, it is hard to imply to the area average inflation dynamics directly from all the separate national regressions. However, one can still derive implications to the total inflation dynamics based on national inflation dynamics. The total area NKPC takes the following form:

$$\pi_t = c + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \alpha x_t + u_t$$

in which π_t is the weighted average inflation rate in the euro area at time t, and x_t is the unemployment rate in the euro area, roughly approximated by the weighted average of national unemployment rates within this union: $x_t = \sum_{i=1}^{N} \omega_i x_{it}$. Although the weighted national inflation dynamics is not directly comparable with the total NKPC model, comparisons of related parameters in these two models can still be informative. For instance, if one expect there would be a 1% increase in the inflation expectations in all nations, the inflation expectations of the euro area will also increase by 1%. According to the two models, we can make two different implications on the aggregate euro area inflation rate. The national specific estimates suggest that the current total inflation rate will increase by $(\sum_{i=1}^{N} w_i \gamma_{f1}^i)\%$, compared to the direct euro area NKPC model estimation, which is referred to as $\pi_f\%$. Meanwhile, notice that the national slackness measurement x_{it} is variant across countries, and one can measure the pressure of total slackness on total inflation rate by adding up national estimates $\sum_{i=1}^{N} w_i \alpha_1^i$ and compare to the national estimate α.

3.2.3 Identification Strategy and Econometric Issues

The national NKPC model has to deal with the endogeneity problem. The national expectations are unobservable, while at the same time, the unemployment rates are potentially endogenous. There might be supply shocks that can both affect national inflation and unemployment. The proxies used to measure the expectation terms are the realized national inflation rates. For each country, one can write down the following regressions:

$$\pi_{it} = c_i + \gamma_{f1}^i \pi_{i,t+1} + \gamma_{b1}^i \pi_{i,t-1} + \gamma_{b2}^i \pi_{t-1} + \alpha_1^i x_{it} + \tilde{u}_{it}$$

where $\tilde{u}_{it} = u_{it} + \gamma_{f1}^i(\pi_{i,t+1}^e - \pi_{i,t+1})$. The potentially endogenous variables in each separate regression are $\pi_{i,t+1}$ and x_{it}. The identification strategy is that for any country i, the error term u_{it} does not depend on any previous information, on both aggregate level and disaggregate level, $E_{t-1}(u_{it}) = 0$. Therefore, the parameters in each regression can be identified and estimated by the linear GMM method.

As lagged variables are valid instruments, and meanwhile, lagged variables are often believed to be relevant instruments due to the persistence of macroeconomic variables. Suppose the instrument set is defined as Z_{it}, thus the moments for the national specific regression are $E(u_{it}Z_{it}) = 0$. If there are p series that are initially correlated with the inflation rate or unemployment rate, the instrument vector Z_{it}

will use from one period lag to M period lag of those p series. In total, there are Mp instruments. There is an infinite number of predetermined variables that can be used as instruments, and different estimation results arise from different choices of instruments. The choice of M is rather arbitrary in the literature [1]. Many macroeconomic variables are persistent, and thus M can be as large as the length of the series T. In the following empirical sections, I set M as the Newey-West HAC estimator truncation number. Consequently, effective instrument selection is necessary for precise estimation, and in the following part, I will show that different instrument sets will result in different estimation results, and imply different patterns for the national and area-wide inflation dynamics.

Within each national NKPC, potential instruments include lagged national and area inflation rates, as well as previous unemployment rates. Due to the necessity of instrument selection in the many-instrument environment, Lasso and kernel-weighted Lasso instrument selection procedures will be applied in separate sector regressions for instrument selection. Detailed procedures have been discussed in the first chapter of this dissertation. The Lasso-type estimators and their l_1 norm property can shrink the coefficients of the redundant instruments to zero in the first stage and automatically select instruments. Moreover, if we assume that more recent variables contain more information than more distant ones to explain the variations in the endogenous variables, the kernel-weighted Lasso instrument selection procedure is designed to

[1] see, for example, [22]

fit in this feature by assigning a higher penalty to more distant instruments. Numerically, it is shown that the GMM estimator of the New Keynesian Phillips curve performs the best in finite samples with instruments selected by the kernel-weighted Lasso. In the empirical results section, GMM estimators with three different instrument selection procedures will be provided: all instruments without selection, Lasso selected instruments, and kernel-weighted Lasso selected instruments.

3.3 Empirical Results

This section shows the data sets that will be used to construct and estimate the national NKPC as well as total euro area NKPC models. GMM estimates with all instruments, selected instruments by Lasso and kernel-weighted Lasso will also be shown. A comparison between the implied euro area results from national estimates and the direct aggregate results will be made.

The data set consists of macroeconomic variables including inflation rates and total unemployment rates. More specifically, Harmonized Indices of Consumer Prices (HICPs) are designed for international comparisons of consumer price inflation. HICP is used for example by the European Central Bank for monitoring of inflation in the Economic and Monetary Union and for the assessment of inflation convergence. In this paper, changes of the HICP excluding energy and food for each country in the euro area and for the whole monetary union will be considered as measures of inflation rates in the NKPC models. Meanwhile, the unemployment rates in specific countries as well as the whole monetary union will be used as measures of slackness in the labor market.

I consider observations on the variables above in the nineteen components of the euro area and the total area from Eurostat website. The raw data in the sample are monthly observations from January 2001 to March 2017. Throughout, inflation is measured in percentage points at an annual rate. The measures of national slackness x_{it} use total unemployment rates in each country.

The euro area is a monetary union of 19 member states which have adopted the euro (€) as their common currency. It consists of Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. The European Central Bank (ECB), which is governed by a president and a board of the heads of national central banks, sets the monetary policy of euro zone. The single mandate of ECB is to stabilize inflation based on the inflation measure using HICP inflation rates.

To gain some perspective on the extent of cross-country heterogeneity within the euro area, figure 1 plots the inflation data of the euro area as well as the 19 member states. The majority of euro area members experienced relatively high inflation in early 2000s. National inflation tended to rise again before 2008 when a global crisis brought inflation in most countries near zero. Despite the overall patterns of inflation dynamics, there exist some "peripheral" countries like Greece, Portugal and Spain having experienced higher inflation rates than other countries like France and Germany. During the period of crisis, these countries have even experienced deflation as reaction to the rising unemployment rate. Similarly, figure 2 reveals remarkable difference in the unemployment rate patterns across countries. In particular, some "peripheral" countries, including Greece, Spain and Ireland, performed quite differently from the rest of the euro area. In general, the observed differences in the patterns of inflation over time make it a challenge for the ECB in its monetary policy formation for the euro area as a whole. Meanwhile, it is more reasonable to consider national data to explain the determinants of the inflation dynamics.

This section starts from the discussion of country-specific New Keynesian Phillips curve estimates. I first show the various specifications of the Phillips curves across countries. Within each specific national regression, I look at the following things: how different instrument selection procedures affect the estimates of parameters, what roles do national and area factors play to affect the inflation dynamics in one country, and how national inflation is influenced by the country's local labor market. Moreover, the country-specific estimates might have important implications for the inflation dynamics estimation in the euro area, as discussed in the model section. A direct estimation of the euro area NKPC is also provided for comparison. Lastly, as pointed out in previous sections, the relation between inflation and economic slackness is changing over time, and a slope change for the euro area NKPC as well as for each country can be observed in split samples.

3.3.1 Country-specific Results

As discussed, the series of previous periods can be treated as relevant and valid instruments due to the persistent effects of macroeconomic variables and the independence between innovations and past information. With 195 monthly observations from 2001M01 to 2017M03, I use up to 4 lags of the area and 19 specific national inflation and unemployment rates as potential instruments. In total, the instrument set includes 160 variables. Tables 14 to 16 show the separate estimates of country-specific NKPC estimates with three different instrument selection procedures respectively: all instruments, Lasso selected instruments and kernel-weighted Lasso selected instruments. Overall, we can notice significant difference of parameter estimates between these three types of estimators. Roughly speaking, if we focus on discussing the differences of the national Phillips curve slopes across countries, we can divide the member countries in the euro area into two categories and discuss the relation between inflation and unemployment among these two categories respectively. The national Phillips curves for countries in the first category have insignificant slopes (α) according to the estimates, where firms' pricing behavior are not significantly affected by the local labor market conditions or economic slackness. While in the second category, the national Phillips curves have significant relation between national inflation and unemployment. Based on the GMM estimates of equation (3.1) with instruments selected by kernel-weighted Lasso, we have the corresponding division of countries as following: flatter Phillips curve countries: Belgium, Germany, Estonia, Ireland, Luxembourg, Netherlands, Austria, Slovenia and Finland; steeper and significant Phillips curve countries: Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Malta, Portugal and Slovakia.

In general, the countries in the euro area are divided into the two categories as shown above based on the estimates' sign and significance of the slope parameter α_1 in each national NKPC. The two divergent effects of national economic slackness on inflation are very interesting, especially in recent literature there are estimates of Phillips curve relationships for the euro area suggesting that the impact of slack on inflation has weakened since the onset of the financial crisis (see, for example, [48] and [49]). Meanwhile, other advanced economies outside the euro are, such as the United States, have also been observed to have relatively stable inflation compared to the rise in unemployment rate during the crisis (see [50], [2]). In order to seek for the explanations of the different reactions of national inflation to the labor market at the country level, I consider more national characteristics from the international trade and national account perspectives. Although not an accurate measure, the current account balance is treated as a measure for the country's international competitiveness, especially for countries experiencing increasing current account deficit, it is a signal for the loss of national competitiveness, domestic macroeconomic imbalances, as well as deeper structural problems [51]. The first category countries behave in a similar way to the whole euro area and the US.

Table 17 shows the annual current account balances as well as the current account balance to GDP ratios for the euro area and each member states based on two sample periods: 2000-2007, and 2008-2016. It is noticeable that most second category countries have experienced consistent current account deficits, like Greece, Spain, Italy and Portugal. While the first category countries most likely have kept external balances in check, for instance, Germany and Netherlands are among the exporting countries whose firms produce more competitive products in the international market. Statistics from table 17 and table 18 show that, for those countries with flatter national Phillips curves, it is more likely for them to experience large current account balance surpluses and focus on export-oriented industry sectors, like Germany, Netherlands or Austria. These countries behave in a similar manner as United States during and after the financial crisis, since in general they share similar characteristics in terms of national account and international specialization. The rise of unemployment in the national labor market has an insignificant impact on national inflation dynamics due to more flexible labor and products markets.

On the other hand, there exist another group of countries whose inflation dynamics are significantly affected by the local labor market conditions, for example, Greece, Spain, Italy or Portugal. These countries have experienced consistent current account deficits and suffered from sovereign debt crisis or financial crisis. The borrowing cost for the firms from these countries are relatively high compared to firms from other countries, due to higher country risk. The negative current account balances suggest that these countries are more import-oriented and less competitive in the international market. Meanwhile, these countries are more likely to have relatively rigid labor and product market. Therefore, when the financial crisis or an adverse aggregate demand hit, exporting firms from these countries might have to deal with a decline in the domestic demand. Even with the presence of home bias preference, the domestic customers may choose to switch to imported goods for lower prices. Faced with high borrowing cost and low domestic as well as international demand, the exporting firms might choose to exit the market, with those surviving ones set their prices following their competitors' previous price setting behavior. Moreover, due to the pressure of international competition, the countries may adjust the specialization in the services sector. The adjustment of specialization makes the firms in these countries rely more on the local labor market conditions, and thus adverse real economic shocks will increase national unemployment rate and impose downward pressure on the inflation rate.

This naturally brings us another aspect to look at the country heterogeneity through country specialization. Over the past two decades, as low-cost competitors have emerged elsewhere in the world, the euro area, like other advanced economies, has recorded some decline in export market shares. Since then, some countries have changed their specialization, but not all did so to the same extent. Table 18 shows the country's specialization with 10 industry breakdowns. I find that there does exist country-specific heterogeneity in the product market, for Germany and Ireland specializing in industry and manufacturing, while Portugal and Italy focusing on wholesale and retail trade, transport or accommodation services. In particular, we find that the countries focusing on industry or manufacturing are more export-oriented. While those other countries specializing in the services sector are more backward-looking with steeper slopes.

There are some more interesting econometric findings by comparing tables 14-16. For example, the estimation of γ^i_{f1} from the national NKPC of the first category countries are higher than those estimates without instrument selection. It implies that firms from those countries are more forward-looking than originally thought. These forward-looking countries behave similarly as US in the sense that the national inflation replies more on future expectations, and inflation expectations become more anchored due to the increased credibility of the ECB to manage inflation expectations.

3.3.2 Euro Area Inflation Dynamics

Disaggregate information can not only provide a better understanding of specific national inflation dynamics, but also have implications for aggregate results. As discussed in the model section, the area aggregate inflation rate is a weighted average of each national inflation rate, with the country weights assumed to be the average of the time-varying national contributions to the total core HICP inflation rate. A time-invariant country weight is imposed in order to compare the implied aggregate estimates in the euro area to the direct estimates obtained only using aggregate information.

We can also obtain the following remarks by comparison as in table 19. First, in the estimation of pure aggregate NKPC estimation, the estimates of γ_f using all three instrument selection procedures show that the aggregate core HICP inflation has a larger forward-looking proportion. Also, the sign of the Phillips curve slope α is negative but not significant, even after using kernel-weighted Lasso procedure to select instruments.

Second, in the estimation of implied aggregate results of the forward-looking parameter $\sum_{i=1}^{N} w_i \gamma_{f1}^{(i)}$, selected instruments suggest that on average in the euro area, inflation is more forward-looking. For instance, GMM estimation of the weighted parameter $\sum_{i=1}^{N} w_i \gamma_{f1}^{(i)}$ with all instruments equal to 0.355, meaning that if future expectation on inflation increases by 1% in every member state of the euro area, this will cause the average inflation rate in the euro area to increase by 0.355%. Meanwhile, in the case of the GMM estimation using kernel-weighted Lasso selected instruments, the proportion estimate increases to 0.638%. These implied estimates of the corresponding forward-looking parameters are significantly different across different instrument selection procedure.

Third, since the GMM estimates with kernel-weighted Lasso instrument selection perform better than other procedures in finite samples, we focus on comparing the direct aggregate and implied aggregate estimates using kernel-weighted Lasso selected instruments. As just mentioned in the first remark, euro aggregate data fails to find a significant trade-off between inflation and unemployment. The Phillips curve has been heavily discussed in recent papers and in the speeches of policy makers, the relation has become flatter and insignificant (see [2], [1] or [28]). However, if we step from the pure aggregate perspective and start to consider disaggregate data, the implied estimates of the slope $\sum_{i=1}^{N} \omega_i \alpha_1^i$ equals to -0.0202 and is significantly different from zero. The insignificance of the pure aggregate model is a result of short span of data (only available after 2000), as well as possible structural breaks of the Phillips curve slope due to financial crisis. The estimation is improved by introducing more disaggregated national level data in order to reduce standard errors of the estimates. Similar to chapter 2, the calculations of the standard errors of the weighted average parameters take cross-country and cross-period correlations of the moments into consideration.

3.3.3 Structural Breaks

As pointed out in previous sections, we cannot find a significant relationship in the euro area New Keynesian Phillips curve if estimated using aggregate data. One possible reason is the time-varying slopes of the Phillips curve and the short sample of the euro area data. There is a growing body of literature suggesting that the Phillips curve in advanced economies has become flatter with inflation rate more anchored to expectations since the financial crisis [2]. This section is to check if there does exist structural changes of the inflation reactions to the changes in the real economy by running the same regressions on split samples. The original sample includes monthly data from January 2001 to March 2017, and since the financial crisis hit global economy, behavior changes have been observed for countries affected by the big negative shock. Thus I divide the original sample into two subsamples: 2001M01 to 2007M08, and 2007M09 to 2017M03, with the breaking point being the approximate beginning of the financial crisis.

Table 20 reports the euro area estimates with kernel weighted Lasso selected instruments based on the two models: the direct aggregate model and the disaggregate national model on the two subsamples. The results provide strong evidence of structural breaks of the Phillips curves within the sample. First, the direct estimate of the area-wide NKPC shows us that the slope of the aggregate Phillips curve is significantly negative with the first half pre-crisis data. The slope estimate has a significant decline since 2007 (from -0.103 to -0.01), and this drop might be one of the reasons for the insignificant estimate of α over the whole sample. We can also observe the significant changes in the estimates of $\sum_{i=1}^{N} \omega_i \gamma_{f1}^i$ before and after the crisis.

One possible explanation of the structural change in the Phillips curve slope is from a recent paper by [52] where they divide firms into two categories based on the firm's internal liquidity: liquidity-constrained firms and liquidity-unconstrained

[2] see, for example, [45]

firms. They argue that the missing disinflation phenomenon after crisis in the United States can be explained by discussing firms' divergent pricing decisions in response to adverse demand or financial shocks based on their balance sheet positions. In the customer markets with a sticky customer base imposed, firms with strong balance sheets will post lower prices to maintain market share, while firms with weak balance sheets can be forced to raise prices, sacrifice its market share, in order to avoid costly external financing. The mixed pricing behavior of firms might contribute to the flatter Phillips curve in the United States after crisis. Analogous to the US, firms from the euro area might face with similar situations. Within the whole area, there exist firms with liquidity constraints or without liquidity constraints. A negative financial or demand shock will cause the "unhealth" firms to deviate from the normal strategy and thus the Phillips curve may become flatter during and after the crisis.

Moreover, both the aggregate and implied aggregate results suggest that the inflation rates in the euro area are more forward-looking in recent years, due to the increased credibility of the central banks' expectation management tools. For example, according to the implied aggregate estimates, a 1% increase in the national inflation expectation across the euro area will only cause the current inflation rate to increase by 0.56% before the crisis, compared to 0.69% during the second half of the sample.

Overall, we can observe structural changes of the relation between inflation and unemployment in the Phillips curve both in the aggregate model and in the implied aggregate model from the national data. The implied aggregate estimates are more efficient compared to the aggregate counterparts. Therefore, in the presence of structural changes, the aggregate data might not be able to provide precise estimates of the Phillips curve due to the data constraint, and making use of the disaggregate data can help improve the estimation performance in finite samples.

3.4 Conclusion

The Phillips curve provides an intuitive framework for assessing the relationship between the level of slack and the rate of inflation in the economy and has been a popular tool for explaining and forecasting inflation dynamics. At the same time, a range of issues, as highlighted in this chapter, suggest that a simple New Keynesian Phillips curve constitutes an insufficient analytical basis to guide monetary policy. This is particularly true for the euro area, whose member states possess heterogeneous economic structure and institutional landscape. Therefore, considering country-specific New Keynesian Phillips curves can result in a better fit within each country and thus provide a better explanation and forecasting performance.

National information is thus introduced to study the national inflation dynamics. In this chapter, we have described a conceptual model to incorporate different market features of various countries. Furthermore, the national model estimates can not only shed light on national specific inflation dynamics, but also have important implications for inflation behavior in the euro area as a whole. In the empirical work, I first improve the finite sample performance of the national estimates in each separate national regression by selecting instruments with kernel-weighted Lasso. I show that there exist both forward-looking inflation dynamics countries as well as backward-looking countries within the euro area. While with the inclusion of the financial crisis data, the Phillips curve slope of many countries of the euro area and the whole area becomes flatter and insignificant, there still exist some countries displaying strong relation between economic slack and the rate of inflation. More interestingly, if we look at the Phillips curve relation of the euro area with disaggregate national variation included, on average, the relation between aggregate inflation and aggregate economic slack is found to be significantly negative.

Table 3.1: Separate National Results: GMM Estimates with All Instruments

Country	γ_{f1}	se(γ_{f1})	γ_{b1}	se(γ_{b1})	γ_{b2}	se(γ_{b2})	α_1	se(α_1)
Belgium	0.000	0.047	0.000	0.041	**1.000**	0.238	0.009	0.054
Germany	**0.460**	0.110	0.361	0.086	0.179	0.070	0.037	0.014
Estonia	**0.577**	0.035	0.309	0.062	0.114	0.038	-0.001	0.007
Ireland	**0.905**	0.128	0.095	0.084	0.000	0.067	-0.011	0.009
Greece	0.000	0.072	0.133	0.082	**0.866**	0.365	0.005	0.022
Spain	0.305	0.036	0.000	0.077	**0.695**	0.172	0.004	0.004
France	0.383	0.202	**0.616**	0.133	0.000	0.110	0.077	0.048
Italy	0.190	0.028	0.000	0.039	**0.810**	0.088	-0.007	0.011
Cyprus	0.499	0.117	0.000	0.105	0.501	0.331	0.017	0.025
Latvia	0.445	0.025	0.133	0.033	0.422	0.050	**-0.019**	0.004
Lithuania	**0.583**	0.023	0.216	0.023	0.201	0.016	**-0.013**	0.004
Luxembourg	**0.677**	0.432	0.323	0.081	0.000	0.352	-0.103	0.069
Malta	0.150	0.048	0.000	0.032	**0.850**	0.324	-0.037	0.116
Netherlands	**0.544**	0.107	0.336	0.123	0.120	0.136	0.275	0.084
Austria	0.284	0.246	**0.716**	0.294	0.000	0.185	-0.131	0.085
Portugal	0.345	0.030	0.016	0.051	**0.639**	0.060	-0.003	0.006
Slovenia	0.329	0.074	0.000	0.176	**0.671**	0.258	0.016	0.027
Slovakia	**0.653**	0.119	0.344	0.098	0.003	0.033	-0.009	0.008
Finland	**0.565**	0.176	0.321	0.110	0.114	0.084	0.115	0.041

Notes: Based on monthly data in the period 2000-2016. This table reports the GMM estimates with all instruments of the national specific NKPC: $\pi_{it} = c_i + \gamma_{f1}^i E_t(\pi_{i,t+1}) + \gamma_{b1}^i \pi_{i,t-1} + \gamma_{b2}^i \pi_{t-1} + \alpha_1^i x_{it} + u_{it}$ as well as the corresponding standard errors for each individual euro area country. The highlighted numbers of γ's stand for the largest proportion between the estimates of γ_{f1},γ_{b1} and γ_{b2}. While the highlighted numbers for the estimates of α_1 represent the countries whose Phillips curve slope estimates are significantly negative (for this table, it means Latvia and Lithuania).

Table 3.2: Separate National Results: GMM Estimates with Lasso-selected Instruments

Country	γ_{f1}	se(γ_{f1})	γ_{b1}	se(γ_{b1})	γ_{b2}	se(γ_{b2})	α_1	se(α_1)
Belgium	0.0000	0.0394	0.0842	0.0285	**0.9158**	0.1595	-0.1266	0.1033
Germany	**0.5367**	0.0753	0.4633	0.0695	0.0000	0.0384	**-0.0260**	0.0072
Estonia	**0.7390**	0.0505	0.1973	0.0599	0.0637	0.0294	0.0023	0.0042
Ireland	**0.5014**	0.0580	0.4986	0.0479	0.0000	0.0452	-0.0010	0.0039
Greece	0.0001	0.0244	0.0000	0.0262	**0.9999**	0.1013	**-0.0249**	0.0067
Spain	0.2994	0.0227	0.0000	0.0649	**0.7006**	0.1362	**-0.0138**	0.0060
France	0.4412	0.0672	**0.5588**	0.0763	0.0000	0.0498	-0.0164	0.0187
Italy	0.2620	0.0255	0.0000	0.0430	**0.7380**	0.0988	**-0.0520**	0.0113
Cyprus	0.3402	0.0322	0.1968	0.0450	**0.4630**	0.1039	**-0.0291**	0.0115
Latvia	**0.5197**	0.0363	0.0483	0.0254	0.4320	0.0315	**-0.0152**	0.0044
Lithuania	**0.5246**	0.0340	0.3182	0.0396	0.1572	0.0279	**-0.0083**	0.0035
Luxembourg	0.0000	0.0370	0.3049	0.0382	**0.6951**	0.0995	0.0871	0.0314
Malta	0.0825	0.0246	0.0954	0.0247	**0.8221**	0.1168	-0.0331	0.0925
Netherlands	**0.5356**	0.0426	0.4644	0.0408	0.0000	0.0638	0.1164	0.0232
Austria	**0.5630**	0.0569	0.4370	0.0826	0.0000	0.0728	-0.0699	0.0291
Portugal	0.3863	0.0301	0.1651	0.0545	**0.4486**	0.0667	**-0.0240**	0.0056
Slovenia	**0.4613**	0.0345	0.2798	0.0680	0.2589	0.0794	0.0283	0.0181
Slovakia	**0.4556**	0.0675	**0.4680**	0.0508	0.0764	0.0186	-0.0060	0.0033
Finland	**0.4909**	0.0582	**0.5091**	0.0505	0.0000	0.0388	-0.0072	0.0194

Notes: Based on monthly data in the period 2000-2016. This table reports the GMM estimates with Lasso selected instruments of the national specific NKPC: $\pi_{it} = c_i + \gamma^i_{f1} E_t(\pi_{i,t+1}) + \gamma^i_{b1}\pi_{i,t-1} + \gamma^i_{b2}\pi_{t-1} + \alpha^i_1 x_{it} + u_{it}$ as well as the corresponding standard errors for each individual euro area country. The highlighted numbers of γ's stand for the largest proportion between the estimates of γ_{f1},γ_{b1} and γ_{b2}. While the highlighted numbers for the estimates of α_1 represent the countries whose Phillips curve slope estimates are significantly negative.

Table 3.3: Separate National Results: GMM Estimates with KLasso-selected Instruments

Country	γ_{f1}	se(γ_{f1})	γ_{b1}	se(γ_{b1})	γ_{b2}	se(γ_{b2})	α_1	se(α_1)
Belgium	0.0000	0.0579	0.0075	0.0259	**0.9925**	0.2142	-0.0716	0.1408
Germany	**1.0000**	0.1586	0.0000	0.0953	0.0000	0.0497	0.0120	0.0121
Estonia	**0.7727**	0.0950	0.1224	0.0763	0.1049	0.0395	-0.0021	0.0048
Ireland	**0.9855**	0.1144	0.0145	0.0734	0.0000	0.0651	-0.0112	0.0083
Greece	0.0001	0.0376	0.0000	0.0443	**0.9999**	0.1614	**-0.0175**	0.0091
Spain	0.3479	0.0299	0.0000	0.0814	**0.6521**	0.1787	0.0058	0.0055
France	**0.8036**	0.1223	0.1964	0.0974	0.0000	0.0531	**-0.0490**	0.0242
Italy	0.3109	0.0409	0.0000	0.0782	**0.6891**	0.1949	**-0.0854**	0.0190
Cyprus	**0.3972**	0.0388	0.2701	0.0529	0.3326	0.1157	-0.0183	0.0108
Latvia	**0.4881**	0.0710	0.0364	0.0417	0.4755	0.0503	-0.0103	0.0066
Lithuania	**0.5138**	0.0573	0.2316	0.0584	0.2546	0.0411	**-0.0194**	0.0049
Luxembourg	**0.9483**	0.1204	0.0000	0.0275	0.0517	0.0764	-0.0155	0.0411
Malta	0.1018	0.0381	0.3198	0.0372	**0.5784**	0.1644	**-0.2292**	0.1134
Netherlands	**0.5619**	0.0734	0.4381	0.0626	0.0000	0.0975	0.0906	0.0253
Austria	**0.6437**	0.0738	0.3563	0.1120	0.0000	0.0985	0.0052	0.0342
Portugal	0.4070	0.0438	0.0000	0.0738	**0.5930**	0.0998	**-0.0232**	0.0068
Slovenia	**0.6129**	0.0487	0.3020	0.0815	0.0851	0.0925	0.0157	0.0149
Slovakia	0.3723	0.0913	**0.5385**	0.0672	0.0892	0.0194	-0.0012	0.0044
Finland	**0.6969**	0.0778	0.3031	0.0657	0.0000	0.0437	0.0229	0.0275

Notes: Based on monthly data in the period 2000-2016. This table reports the GMM estimates with Kernel Lasso selected instruments of the national specific NKPC: $\pi_{it} = c_i + \gamma_{f1}^i E_t(\pi_{i,t+1}) + \gamma_{b1}^i \pi_{i,t-1} + \gamma_{b2}^i \pi_{t-1} + \alpha_1^i x_{it} + u_{it}$ as well as the corresponding standard errors for each individual euro area country. This table uses the Parzen kernel weighting function. The highlighted numbers of γ's stand for the largest proportion between the estimates of γ_{f1},γ_{b1} and γ_{b2}. While the highlighted numbers for the estimates of α_1 represent the countries whose Phillips curve slope estimates are significantly negative.

Table 3.4: National Current Account Balances

GEO/TIME	Whole Sample	2001-2007	2008-2016	Whole Sample	2001-2007	2008-2016
Euro area	79173.9	13490.7	130260.8	0.9%	0.2%	1.3%
Belgium	2163.6	7844.3	-992.4	0.6%	2.6%	-0.3%
Germany	143376.3	82517.3	190711.1	5.6%	3.6%	6.9%
Estonia	-565.6	-1300.1	5.6	-3.9%	-12.3%	0.0%
Ireland	-1104.9	-4643.0	1253.9	-0.6%	-2.9%	0.6%
Greece	-16428.9	-19876.5	-14130.4	-8.3%	-10.4%	-7.0%
Spain	-35494.8	-57524.9	-18360.2	-3.6%	-6.6%	-1.7%
France	-6593.8	8319.6	-18193.1	-0.3%	0.5%	-0.9%
Italy	-8905.4	-9908.0	-8125.7	-0.6%	-0.7%	-0.5%
Cyprus	-1292.6	N.A.	-1292.6	-7.8%	0.0%	-6.9%
Latvia	-1037.1	-1868.4	-390.6	-5.6%	-13.7%	-1.8%
Lithuania	-1131.8	-2463.9	-539.7	-4.1%	-12.5%	-1.6%
Luxembourg	2709.1	2797.8	2640.2	7.1%	9.6%	5.9%
Malta	45.2	-245.1	174.2	0.7%	-4.9%	2.3%
Netherlands	47915.3	39205.8	52753.9	8.0%	7.3%	8.1%
Austria	6410.5	5284.6	7286.2	2.2%	2.1%	2.3%
Portugal	-10458.4	-14279.1	-7486.8	-6.3%	-9.3%	-4.2%
Slovenia	179.1	-470.6	684.4	0.5%	-1.7%	1.8%
Slovakia	-1999.1	-3828.0	-1186.2	-3.5%	-10.5%	-1.6%
Finland	3258.2	8390.8	-733.9	1.8%	5.2%	-0.4%

Source: Eurostat.
Notes: This table reports the annual current account balances and current account to GDP ratios based on three different samples: the whole sample: 2001-2016, and two subsamples: 2001-2007, 2008-2016.

Table 3.5: National Gross Income by Industry: 2017Q1 in million euro

GEO	Agriculture	Industry	Manufacturing	Construction	Wholesale	Information	Financial activities	Real estate	Technical activities	Public administration	other services
Belgium	767	16150	:	5351	18656	3984	5724	8014	13645	**21529**	2192
Germany	5091	**181292**	160198	34581	111701	34378	27525	77215	80194	132169	28957
Estonia	132.3	966.1	730.4	320.8	**1029.6**	293.7	183.5	458.9	433.1	760.7	126.3
Ireland	655.7	**23162.2**	21923.1	1887.2	8177.1	6697.6	4561.4	4136.5	8234.7	7554.7	792.3
Greece	1567.8	5503.3	3969.8	720	**9503.6**	1318.5	1726.8	6767	1823.8	7976.5	1597.7
Spain	6637	46839	36790	14652	**60500**	10630	9849	28134	23116	48137	10236
France	8037	70455	57388	27782	89020	26578	20131	65796	67011	**114209**	15055
Italy	8285.6	72244.5	60723.9	17973.1	**79864.2**	12989.4	19181.9	52821.7	36125.6	63612	14656.9
Cyprus	93.3	306.5	203.3	167.1	**1037.2**	192.7	406.3	397.8	407.5	818	175.6
Latvia	185.9	988	740.4	303.3	**1444.5**	275.6	241.8	730.5	435.4	907.6	185.6
Lithuania	280.7	2028.5	1738.2	603.3	**2914.8**	320.9	187.9	588.4	599.5	1299.3	198.1
Luxembourg	31.7	855.9	655.4	603.9	2265.3	951.2	**3320.4**	949	1501.6	1952.6	212.5
Malta	27.2	236.1	195.5	86.6	**457.9**	151.8	158	119.3	285.3	396	317.9
Netherlands	3301.2	23708	19294.2	7661.1	**34841.8**	7629.4	10874.1	10128.5	24864.2	33943.1	4303.2
Austria	988.1	17276.5	14858.4	5252.8	**18481.1**	2733.2	3116.7	8386.5	7553.6	13866.2	2252.5
Portugal	896.6	7643.1	5709.1	1727.6	**10115.4**	1387.1	2039.9	4951.7	3077.5	7919.6	1220.8
Slovenia	206	**2463.6**	2140.8	439.9	1860.5	385	349.8	606.9	905.2	1483.9	236.6
Slovakia	:	:	:	:	:	:	:	:	:	:	:
Finland	1314	**10073**	8462	3311	7574	2764	1465	6128	4119	9835	1464

Source: Eurostat. The above industries are short for the following full definitions. Agriculture: Agriculture, forestry and fishing; Industry: exclude construction; Wholesale: Wholesale and retail trade, transport, accomodation and food service activities; Information: Information and communication; Financial activities: Financial and insurance activities; Technical activities: Professional, scientific and technical activities; administrative and support service activities; Public administration: Public administration, defence, education, human health and social work activities; other services: Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies

Table 3.6: Euro Area Estimates Comparison: All 3 Instrument Selection Procedures

	GMM		Lasso		Klasso	
parameters	estimates	s.e.	estimates	s.e.	estimates	s.e.
γ_f	0.666	0.032	0.700	0.030	0.698	0.016
$\sum_{i=1}^{N} \omega_i \gamma_{f1}$	0.355	0.049	0.401	0.031	0.638	0.059
α	-0.014	0.016	-0.024	0.028	-0.037	0.022
$\sum_{i=1}^{N} \omega_i \alpha_1^i$	0.037	0.013	-0.024	0.007	-0.020	0.010

Notes: Based on monthly data in the period 2000-2016. This table reports the estimation of the euro area NKPC parameters using aggregate data only in the aggregate model: $\pi_t = c + \gamma_f E_t(\pi_{t+1}) + (1-\gamma_f)\pi_{t-1} + \alpha x_t + u_t$, as well as the weighted parameters obtained by estimating the national specific NKPC: $\pi_{it} = c_i + \gamma_{f1}^i E_t(\pi_{i,t+1}) + \gamma_{b1}^i \pi_{i,t-1} + \gamma_{b2}^i \pi_{t-1} + \alpha_1^i x_{it} + u_{it}$. Correspondingly, the standard errors are also reported. This table uses the Parzen kernel weighting function for KLasso instrument selection.

Table 3.7: Structural Break: Comparisons of KLasso Estimates on Subsamples

	Subsample 1: 2001-2007		Subsample 2: 2008-2016	
parameters	estimates	s.e.	estimates	s.e.
γ_f	0.6263	0.0311	0.7246	0.0191
$\sum_{i=1}^{N}\omega_i\gamma_{f1}$	0.5554	0.0449	0.6939	0.1149
α	-0.1038	0.0575	-0.0102	0.0389
$\sum_{i=1}^{N}\omega_i\alpha_1^i$	-0.0434	0.0200	-0.0165	0.0291

Notes: Based on monthly data in two subsamples: 2001-2007, 2008-2016. This table reports the kernel weighted Lasso estimation of the euro area NKPC parameters using aggregate data only in the aggregate model: $\pi_t = c+\gamma_f E_t(\pi_{t+1})+(1-\gamma_f)\pi_{t-1}+\alpha x_t + u_t$, as well as the weighted parameters obtained by estimating the national specific NKPC: $\pi_{it} = c_i + \gamma_{f1}^i E_t(\pi_{i,t+1}) + \gamma_{b1}^i\pi_{i,t-1}+\gamma_{b2}^i\pi_{t-1}+\alpha_1^i x_{it}+u_{it}$. Correspondingly, the standard errors are also reported. This table uses the Parzen kernel weighting function for KLasso instrument selection.

Figure 3.1: National Inflation

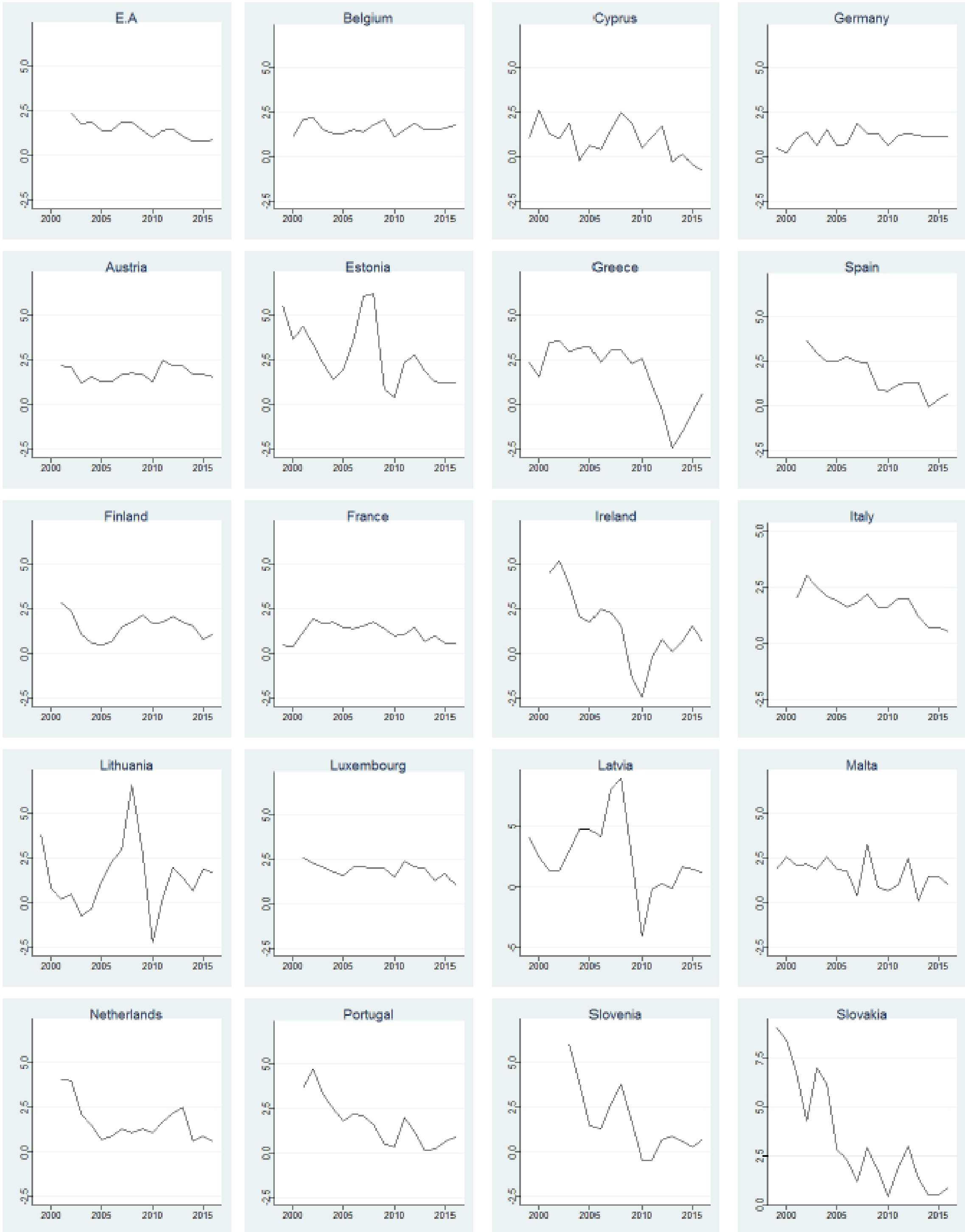
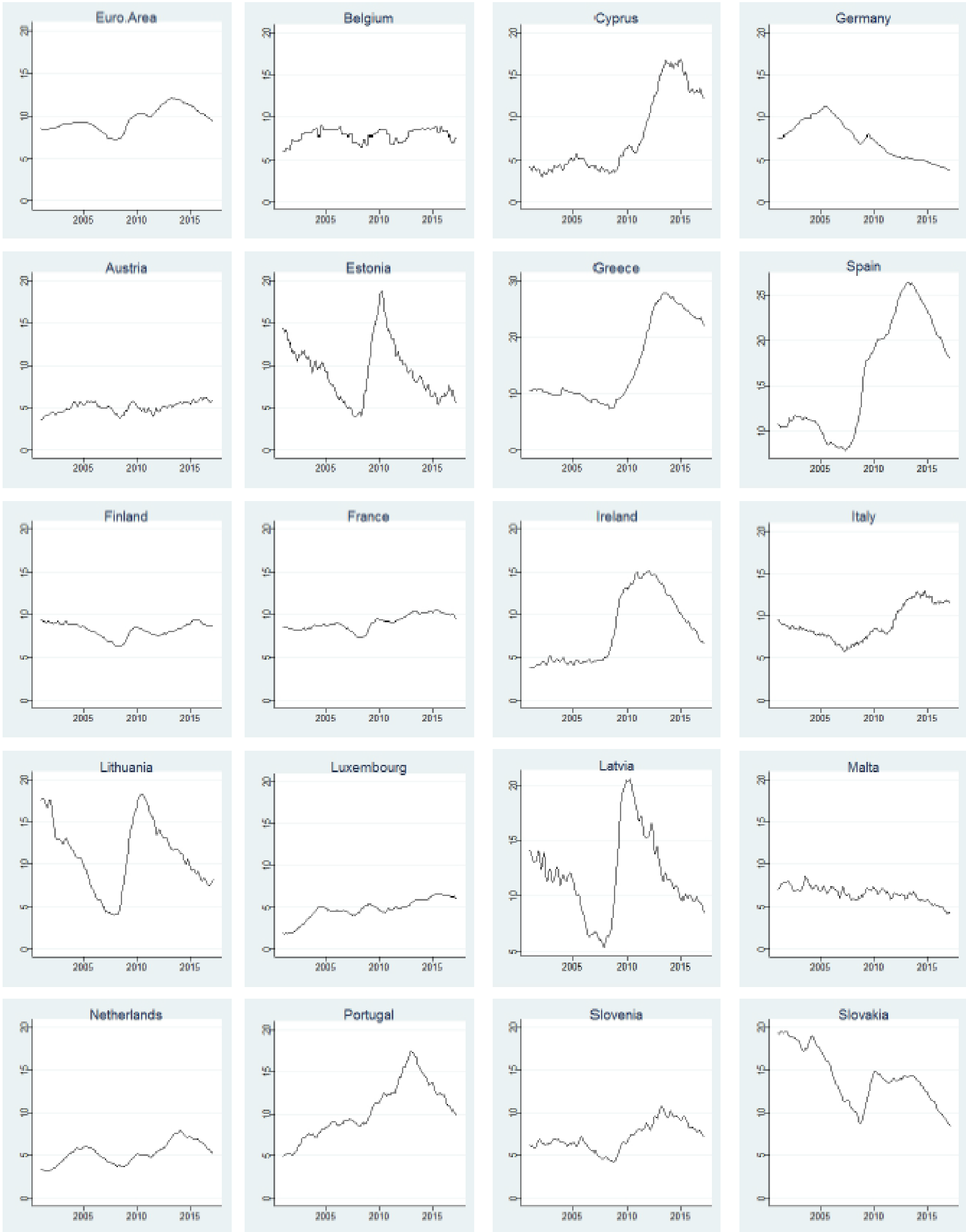


Figure 3.2: National Unemployment Rate



Appendix A

Appendix to Chapter 1

In this appendix, we provide a full derivation of regional New Keynesian Phillips curve.

The model derived here is an extension of previous work on New Keynesian model in the open economy by [15] by adding the backward-looking pricing rules of firms into the regional model.

Suppose the national economy is modeled with a continuum of small regions, represented by the unit interval. The measure of each region is zero. Different economies are subject to different productivity shocks. Each region has a representative household and a continuum of firms producing a differentiated good, also represented by the unit interval. Compared to the rest of the nation, the performance of each single region does not have any impact on the national economy. Also, each region is assumed to be symmetric in terms of identical consumer preferences and firm pricing behavior.

I discuss the macroeconomic variables in the home region H. All other variables with subscript $i \in [0,1]$ refer to region i. Region F represents a general notation for all other region $i \in [0,1]$ outside region H. Taking $C^i_{H,t}$ as an example, the subscript $\{H,t\}$ represents the consumption good produced in region H at period t, and the superscript i represents the good is finally consumed in the market of region i. Also the superscript H is omitted for notation simplicity.

A.1 Households

A typical region H is inhabited by a representative household who maximizes

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, N_t) \tag{A.1}$$

where N_t denotes the hours of labor, and C_t is a composite consumption bundle index defined by

$$C_t \equiv [(1-\alpha)^{\frac{1}{\eta}}(C_{H,t})^{\frac{\eta-1}{\eta}} + \alpha^{\frac{1}{\eta}}(C_{F,t})^{\frac{\eta-1}{\eta}}]^{\frac{\eta}{\eta-1}} \tag{A.2}$$

where α captures the region bias of household's consumption and η is the substitution elasticity of the goods consumption between region H and the rest regions, labeled as F. $C_{H,t}$ is an index of consumption of goods produced in region H given by the constant elasticity of substitution function

$$C_{H,t} \equiv (\int_0^1 C_{H,t}(j)^{1-\frac{1}{\epsilon}} dj)^{\frac{\epsilon}{\epsilon-1}}$$

where $j \in [0,1]$ denotes the good variety. Similarly, $C_{F,t}$ is a composite index of consumption of goods produced in the other regions $i \in [0,1], i \neq H$, given by

$$C_{F,t} \equiv (\int_0^1 (C_{i,t})^{1-\frac{1}{\gamma}} di)^{\frac{\gamma}{\gamma-1}}$$

where $C_{i,t}$ is an index of the quantity of goods consumed by household in region H that were produced in region i. By analogy, the consumption index is given by the same CES function

$$C_{i,t} \equiv (\int_0^1 C_{i,t}(j)^{1-\frac{1}{\epsilon}} dj)^{\frac{\epsilon}{\epsilon-1}}$$

The parameters are explained as follows. ε denotes the elasticity of substitution between goods produced within any given region. Parameter α again is interpreted as the home bias of household's consumption. Parameter $\eta > 0$ measures the elasticity of substitution between home made goods or other region made goods, and lastly γ measures the substitutability between goods produced in other regions.

The maximization of the utility function is subject to the following budget constraint:

$$\int_0^1 P_{H,t}(j)C_{H,t}(j)dj + \int_0^1\int_0^1 P_{i,t}(j)C_{i,t}(j)djdi + E_t[Q_{t,t+1}D_{t+1}] \leq D_t + W_tN_t + T_t \tag{A.3}$$

for $t = 1, 2, \cdots$ where $P_{H,t}(j)$ is the market price of good j produced in region H, while $P_{i,t}(j)$ is the price of good j produced in region i. Note that due to the Law of One Price, consumers from different regions should be able to buy the same good with the same price, i.e. $P_{i,t}(j) = P^i_{i,t}(j)$, and $P^i_{H,t}(j) = P_{H,t}(j)$. Therefore, the superscripts of the price indices are omitted due to LOOP. N_t denotes hours of work, W_t is the nominal wage, T_t denotes the lump-sum transfers/taxes, and D_{t+1} is the nominal payoff in period $t+1$ of portfolio held at the end of period t. $Q_{t,t+1}$ is the stochastic discount factor(SDF) between period t and $t+1$. Assume that households have access to a complete set of contingent claims, traded nationally.

Now the household must decide how to allocate the consumption expenditures among the differentiated goods within the same region, given the total expenditures spent on goods produced in the same region. The households maximize the consumption index $C_{H,t}$:

$$\max \quad C_{H,t} \qquad s.t.$$
$$\int_0^1 P_{H,t}(j)C_{H,t}(j)dj \equiv Z_{H,t}$$

where we can write down the Lagrangian equation and derive the first order condition for every good produced in region H, and thus obtain the demand equation for each firm j in a given region:

$$C_{H,t}(j) = (\frac{P_{H,t}(j)}{P_{H,t}})^{-\varepsilon} C_{H,t}; C_{i,t}(j) = (\frac{P_{i,t}(j)}{P_{i,t}})^{-\varepsilon} C_{i,t} \tag{A.4}$$

where the second equality can be obtained similarly as the demand function for each firm j in sector i by households from the home region. $P_{H,t} = (\int_0^1 P_{H,t}(j)^{1-\varepsilon} dj)^{\frac{1}{1-\varepsilon}}$ is the region H's producer price index and $P_{i,t} = (\int_0^1 P_{i,t}(j)^{1-\varepsilon} dj)^{\frac{1}{1-\varepsilon}}$ is the price index for goods consumed by household in region H but produced in region i. It can also be shown that $\int_0^1 P_{H,t}(j) C_{H,t}(j) dj = P_{H,t} C_{H,t}$ and $\int_0^1 P_{i,t}(j) C_{i,t}(j) dj = P_{i,t} C_{i,t}$.

Furthermore, the allocation of consumption for household in region H among the goods produced in other regions can be similarly decided:

$$\max \quad C_{F,t} \qquad w.r.t. \quad C_{i,t}$$
$$\int_0^1 P_{i,t} C_{i,t} di \equiv Z_{F,t}$$

and hence the allocation can be derived:

$$C_{i,t} = (\frac{P_{i,t}}{P_{F,t}})^{-\gamma} C_{F,t} \tag{A.5}$$

where $P_{F,t} \equiv (\int_0^1 P_{i,t}^{1-\gamma} di)^{\frac{1}{1-\gamma}}$ is the price index for all consumed goods produced in other regions. Notice that $\int_0^1 C_{i,t} P_{i,t} di = C_{F,t} P_{F,t}$.

Finally, the optimal allocation of expenditures between goods produced in home region or other regions $C_{H,t}, C_{F,t}$ is decided by

$$\max C_t \quad w.r.t. \quad C_{H,t}, C_{F,t}$$

$$s.t. \quad P_{H,t} C_{H,t} + P_{F,t} C_{F,t} \equiv Z_t$$

By writing down the Lagrangian equation and the optimal allocation of expenditures between regions is

$$C_{H,t} = (1-\alpha)(\frac{P_{H,t}}{P_t})^{-\eta} C_t; C_{F,t} = \alpha(\frac{P_{F,t}}{P_t})^{-\eta} C_t \tag{A.6}$$

where $P_t = [(1-\alpha)(P_{H,t})^{1-\eta} + \alpha(P_{F,t})^{1-\eta}]^{\frac{1}{1-\eta}}$ is the regional CPI. Accordingly, the period budget constraint can be rewritten as

$$P_t C_t + E_t[Q_{t,t+1} D_{t+1}] \leq D_t + W_t N_t + T_t \tag{A.7}$$

Moreover, assume the utility function has the form $U(C_t, N_t) = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi}$. Then the intra-temporal optimal condition is obtained from the trade-off between consumption and labor within the same period, i.e. the complete differential of C_t

and N_t should satisfy both the objective function and the budget constraint:

$$C_t^{\sigma} N_t^{\varphi} = \frac{W_t}{P_t} \tag{A.8}$$

Meanwhile, the inter-temporal optimal condition can be derived from the trade-off of consumptions of period t and $t+1$:

$$\beta(\frac{C_{t+1}}{C_t})^{-\sigma}(\frac{P_t}{P_{t+1}}) = Q_{t,t+1} \tag{A.9}$$

Taking conditional expectation on both sides:

$$Q_t = \beta E_t[(\frac{C_{t+1}}{C_t})^{-\sigma}(\frac{P_t}{P_{t+1}})] \tag{A.10}$$

where $Q_t \equiv E_t[Q_{t,t+1}]$denotes the price of a one-period discount bond paying off one unit of currency in $t+1$. The above equation will be used to discover the relation of consumptions across regions. The two optimal conditions can be respectively written in log-linearized form as

$$w_t - p_t = \sigma c_t + \varphi n_t \tag{A.11}$$

$$c_t = E_t(c_{t+1}) - \frac{1}{\sigma}(i_t - E_t(\pi_{t+1}) - \rho) \tag{A.12}$$

Aside from the above optimal conditions from the consumer's decision making, one would like to know the relations between the identities mentioned above. Bilateral relative prices between region H and region i is defined as $S_{i,t} = \frac{P_{i,t}}{P_{H,t}}$ and the effective relative prices are given by

$$\begin{aligned} S_t &\equiv \frac{P_{F,t}}{P_{H,t}} \\ &= (\int_0^1 S_{i,t}^{1-\gamma} di)^{\frac{1}{1-\gamma}} \end{aligned}$$

which can be approximated around a symmetric steady state satisfying $S_{i,t} = 1$ for all $i \in [0, 1]$ by

$$s_t = \int_0^1 s_{i,t} di \tag{A.13}$$

where $s_t = logS_t = p_{F,t} - p_{F,t}$. Again starting from the CPI and rewrite the fomula:

$$P_t = [(1-\alpha)(P_{H,t})^{1-\eta} + \alpha(P_{F,t})^{1-\eta}]^{\frac{1}{1-\eta}}$$

The log linearization can be done by approximating around the steady state where all price indices are constant: $P_t = P_{H,t} = P_{F,t} = P_0$. Suppose $p_t = log(P_t)$, $p_{H,t} = log(P_{H,t})$ and $p_{F,t} = log(P_{F,t})$,

$$exp(p_t) = [(1-\alpha)(exp(p_{H,t}))^{1-\eta} + \alpha(exp(p_{F,t}))^{1-\eta}]^{\frac{1}{1-\eta}}$$

The approximation around the steady state is

$$p_t = (1-\alpha)p_{H,t} + \alpha p_{F,t} \tag{A.14}$$

Assume $\pi_{H,t} = p_{H,t} - p_{H,t-1}$ and $\pi_t = p_t - p_{t-1} = (1-\alpha)\pi_{H,t} + \alpha\pi_{F,t}$.

Due to the Law of One Price, consumers from different regions should be able to buy the same good with the same price, i.e. $P_{i,t}(j) = P^i_{i,t}(j)$ and thus $P_{F,t} = P^i_{F,t}$. The superscript i represents that the specified good is consumed by household in region i. Then we have the following identities between the composite $p_{F,t} = \int_0^1 p_{i,t}di = \int_0^1 p^i_{i,t}di = p^*_t$, where p^*_t is the national CPI. Moreover, assume the relative regional CPI is defined as $R_{i,t} \equiv \frac{P^i_t}{P_t}$, and let $R_t = \int_0^1 R_{i,t}di$. It follows that $r_t = logR_t = \int_0^1 (p^i_t - p_t)di = (1-\alpha)s_t$.

Revisiting the inter-temporal condition for households of region H:

$$\beta(\frac{C_{t+1}}{C_t})^{-\sigma}(\frac{P_t}{P_{t+1}}) = Q_{t,t+1}$$

and by the symmetry of households from different regions

$$\beta(\frac{C^i_{t+1}}{C^i_t})^{-\sigma}(\frac{P^i_t}{P^i_{t+1}}) = Q_{t,t+1} = \beta(\frac{C_{t+1}}{C_t})^{-\sigma}(\frac{P_t}{P_{t+1}}) \tag{A.15}$$

for all t. Therefore, by rearranging the two sides the above equation, the following relation holds for all t,

$$(\frac{C_t^i}{C_t})^{\sigma}(\frac{P_t^i}{P_t}) = (\frac{C_{t+1}^i}{C_{t+1}})^{\sigma}(\frac{P_{t+1}^i}{P_{t+1}})$$

$$C_t = \vartheta_i C_t^i R_{i,t}^{\frac{1}{\sigma}} \tag{A.16}$$

where $\vartheta_i = 1$ as we assume symmetric initial conditions. Taking logs on both sides and integrating over i yields

$$c_t = c_t^* + \frac{1}{\sigma} r_t = c_t^* + \frac{1-\alpha}{\sigma} s_t \tag{A.17}$$

A.2 Firms

Assume a typical firm from region H produces a differentiated good represented by the production function (constant returns to scale)

$$Y_t(j) = A_t N_t(j)$$

where $j \in [0,1]$ is a firm-specific index, and where $a_t \equiv logA_t$ follows the AR(1) process $a_t = \rho_a a_{t-1} + \epsilon_{a,t}$. And the real marginal cost will be common across all firms in region H and given by $mc_t = w_t - p_{H,t} - a_t$.

We assume that firms from region H set prices as follows. In each period, $1-\theta$ random selected firms will set new prices, while the rest of the firms do not adjust prices, with an individual firm's probability of re-optimizing in any given period being independent of the time elapsed since it last reset its price. Meanwhile, a fraction $1-w$ of the firms, which we refer to as forward-looking firms, choose the price that maximizes the current market value of the profits generated while that price remains effective. The remaining firms, of measure w, which we refer to as backward-looking, instead use a simple rule of thumb that is based on recent aggregate pricing behavior.

Suppose at period t and in region H, if the firm is "randomly selected" to reset its price, a forward-looking firm will choose the price $P^f_{H,t}$, while the backward-looking firm will pick $P^b_{H,t}$. Let $S(t) \subset [0,1]$ represent the set of firms not re-optimizing the price in period t. $S_f(t) \subset S^c(t)$ represents the set of forward-looking firms who re-optimize its price in period t, and $S_b(t) \subset S^c(t)$ is the backward-looking firms re-optimizing the price in period t.

$$\begin{aligned}
P_{H,t} &= [\int_0^1 P_{H,t}(j)^{1-\varepsilon} dj]^{\frac{1}{1-\varepsilon}} \\
&= [\int_{S(t)} P_{H,t-1}(j)^{1-\varepsilon} dj + \int_{S_f(t)} (P^f_{H,t})^{1-\varepsilon} dj + \int_{S_b(t)} (P^b_{H,t})^{1-\varepsilon} dj]^{\frac{1}{1-\varepsilon}} \\
&= [\theta(P_{H,t-1})^{1-\varepsilon} + (1-\theta)(1-w)(P^f_{H,t})^{1-\varepsilon} + (1-\theta)w(P^b_{H,t})^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}}
\end{aligned}$$

And the log-linearization of the above formula around the steady state follows:

$$p_{H,t} = \theta p_{H,t-1} + (1-\theta)[(1-w)p^f_{H,t} + wp^b_{H,t}] \tag{A.18}$$

where the index for newly set prices can be expressed as $\bar{p}^*_{H,t} = (1-w)p^f_{H,t} + wp^b_{H,t}$.

And hence $p_{H,t} = \theta p_{H,t-1} + (1-\theta)\bar{p}^*_{H,t}$.

$$\pi_{H,t} = p_{H,t} - p_{H,t-1} = (1-\theta)(\bar{p}^*_{H,t} - p_{H,t-1}) \tag{A.19}$$

and similarly, $\pi^i_{i,t} = (1-\theta)(\bar{p}^*_{i,t} - p^i_{i,t})$. Therefore, the regional CPI $p_t = (1-\alpha)p_{H,t} + \alpha p_{F,t} = \theta p_{t-1} + (1-\theta)[(1-\alpha)\bar{p}^*_{H,t} + \alpha \int_0^1 \bar{p}^*_{i,t} di]$ and the regional inflation rate $\pi_t = (1-\alpha)\pi_{H,t} + \alpha \pi_{F,t}$, where $\pi_{F,t} = \int_0^1 \pi^i_{i,t} di = \int_0^1 (1-\theta)(\bar{p}^*_{i,t} - p^i_{i,t}) di$.

Therefore, the regional inflation π_t can be decomposed into two parts: $\pi_t = A+B$, where $A = (1-\alpha)(1-\theta)[(1-w)(p^f_{H,t} - p_{H,t-1}) + w(p^b_{H,t} - p_{H,t-1})]$, $B = \alpha(1-\theta)[\int_0^1 \bar{p}^*_{i,t} di - p_{F,t-1}] = \alpha(1-\theta)[\int_0^1 (1-w)(p^f_{i,t} - p^i_{i,t-1}) + w(p^b_{i,t} - p^i_{i,t-1}) di]$.

The forward-looking rule of firms in region H is identical to the firms in Calvo model:

$$p^f_{H,t} = (1-\beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k E_t(\hat{mc}_{t+k} + p_{H,t+k}) \tag{A.20}$$

where $\hat{mc}_{t+k}$ denotes the difference between the real marginal cost at time $t+k$ and its steady state value, and it can be derived that

$$p^f_{H,t} - p_{H,t-1} = (1-\beta\theta)\hat{mc}_t + \pi_{H,t} + \beta\theta(p^f_{H,t+1} - p_{H,t})$$

Similarly, the forward-looking pricing rule for firms from region i follows:

$$p^f_{i,t} - p_{i,t-1} = (1-\beta\theta)\hat{mc}^i_t + \pi^i_{i,t} + \beta\theta(p^f_{i,t+1} - p^i_{i,t}) \tag{A.21}$$

On the other side, the backward-looking firms reset the prices based on the behavior of all potential competitors in its own region. For example, firms from region H will follow the following backward-looking rule:

$$p^b_{H,t} = (1-\alpha)\bar{p}^*_{H,t-1} + \alpha\bar{p}^*_{F,t-1} + \pi_{t-1} \tag{A.22}$$

And by using the identities discussed above,

$$p^b_{H,t} - p_{H,t-1} = \frac{\pi_{t-1}}{1-\theta} + \alpha(p_{F,t-1} - p_{H,t-1}) \tag{A.23}$$

Similarly, the backward-looking rule for firms from other region i follows:

$$p^b_{i,t} - p_{i,t-1} = \frac{\pi^i_{t-1}}{1-\theta} + \alpha(p_{F,t-1} - p^i_{i,t-1}) \tag{A.24}$$

Plugging all the above equations into A and B and this will allow us to derive the inflation dynamics as

$$\begin{aligned}
[\theta + w - \theta w + \theta w\beta(1-\alpha)]\pi_t = \beta\theta E_t(\pi_{t+1}) + (1-\alpha)w\pi_{t-1} + \alpha w\pi_{F,t-1} - \beta\theta\alpha w\pi_{F,t} \\
+(1-\beta\theta)(1-\theta)(1-w)[(1-\alpha)\hat{mc}_t + \alpha\hat{mc}^F_t] \\
-\beta\theta\alpha w(1-\alpha)(1-\theta)E_t(s_{t+1}) + \alpha w(1-\alpha)(1-\theta)s_t
\end{aligned}$$

where we still need to know the relations between real marginal cost, relative prices and regional output. Notice that the parameter in front of π_t roughly equals to the sum of the parameters for $E_t(\pi_{t+1}), \pi_{t-1}, \pi_{F,t-1}$ and $\pi_{F,t}$ when β is close to 1. This presents a theoretical reason to assume that the coefficients in front of all the inflation terms sum up to one in the specification of the regional NKPC model.

A.3 Equilibrium

First on the demand side, for region H, the goods market clearing requires:

$$Y_t(j) = C_{H,t}(j) + \int_0^1 C_{H,t}^i(j)di$$

where $C_{H,t}^i(j)$ denotes region i's demand for good j produced in the home region. Plugging into the aggregate regional output $Y_t \equiv [\int_0^1 Y_t(j)^{1-\frac{1}{\varepsilon}}dj]^{\frac{\varepsilon}{\varepsilon-1}}$ yields

$$Y_t = (\frac{P_{H,t}}{P_t})^{-\eta} C_t[(1-\alpha) + \alpha \int_0^1 S_t^{\gamma-\eta} R_{i,t}^{\eta-\frac{1}{\sigma}} di] \tag{A.25}$$

Taking the first order log-linear approximation around the symmetric steady state,

$$y_t = c_t + \frac{\alpha}{\sigma}[\alpha\gamma + (1-\alpha)(\sigma\eta - 1)]s_t = c_t + \frac{\alpha}{\sigma}\omega s_t \tag{A.26}$$

where $\omega = \alpha\gamma + (1-\alpha)(\sigma\eta - 1)$, and similarly

$$y_t^i = c_t^i + \frac{\alpha}{\sigma}\omega s_t^i \tag{A.27}$$

The aggregate national output $y_t^* = \int_0^1 y_t^i di = c_t^*$, and therefore, $y_t = y_t^* + \frac{1+\alpha(\omega-1)}{\sigma} s_t$. Suppose $\sigma_\alpha \equiv \frac{\alpha}{1+\alpha(\omega-1)}$, and thus $s_t = \sigma_\alpha(y_t - y_t^*)$.

From the supply side, the aggregate employment

$$N_t \equiv \int_0^1 N_t(j)dj = \frac{Y_t}{A_t}\int_0^1 (\frac{P_{H,t}(j)}{P_{H,t}})^{-\varepsilon} dj \tag{A.28}$$

and up to a first-order approximation, $y_t = a_t + n_t$.

Next the real marginal cost

$$\begin{aligned} mc_t &= (w_t - p_{H,t}) - a_t \\ &= (w_t - p_t) + (p_t - p_{H,t}) - a_t \\ &= \sigma(y_t^* + \frac{1-\alpha}{\sigma} s_t) + \varphi(y_t - a_t) + \alpha s_t - a_t \\ &= (\sigma - \sigma_\alpha)y_t^* + (\varphi + \sigma_\alpha)y_t - (1+\varphi)a_t \\ &= (\sigma - \sigma_\alpha)n_t^* + (\varphi + \sigma_\alpha)n_t - (1-\sigma_\alpha)a_t + (\sigma - \sigma_\alpha)a_t^* \end{aligned}$$

Similarly, $mc_t^i = (\sigma - \sigma_\alpha)n_t^* + (\varphi + \sigma_\alpha)n_t^i - (1-\sigma_\alpha)a_t^i + (\sigma - \sigma_\alpha)a_t^*$, and $mc_t^F = \int_0^1 mc_t^i di = (\sigma + \varphi)n_t^* - (1-\sigma)a_t^*$.

Finally, since we already know that $s_t = \sigma_\alpha(y_t - y_t^*)$, $E_t(s_{t+1})$ should depend on the expected regional and national output.

Overall, by replacing the equilibrium conditions, one can conclude that equation (A.25) can be further interpreted as the following: the current regional inflation rate is affected by its own future expectations, previous regional inflation rate, previous national inflation rate, current national inflation rate, as well as regional and national employment growth rate. Furthermore, it is assumed that x_t is the unemployment rate and thus $x_t = 1 - \frac{N_t}{LFP_t}$. Approximately, the following relation holds: $x_t = log(1 - x_t) = log(N_t) - log(LFP_t) = n_t - Constant$. Thus the inflation can be linked to the unemployment rate.

A.4 Implications to the Regional NKPC Model

From the model above, we are able to derive the New Keynesian Phillips curve for regions as:

$$\pi_{it} = c + \gamma_f E_t(\pi_{i,t+1}) + \gamma_{b1}\pi_{i,t-1} + \gamma_{b2}\pi_{t-1} + \gamma_c \pi_t + \alpha_1 x_{it} + \alpha_2 x_t + u_{it} \tag{A.29}$$

Intuitively speaking, current regional inflation is affected by the first four terms is because of the mixed pricing behavior of firms and the regional goods market consuming all goods produced nationally. Meanwhile, the current national inflation might drive current regional inflation due to inflation persistence. Lastly, regional inflation dynamics is also affected by regional and national unemployment rates through the channel of real marginal costs.

The model suggests that current national inflation rate also has effect on current regional inflation rate. Since the national variables are considered as the integral of the regional variables for any $i \in [0, 1]$. Taking integral from 0 to 1 on both sides of equation(1.17), the regional NKPC model can imply the national inflation follows the dynamics below:

$$\pi_t = \frac{c}{1-\gamma_c} + \frac{\gamma_f}{1-\gamma_c} E_t(\pi_{t+1}) + \frac{\gamma_{b1}+\gamma_{b2}}{1-\gamma_c}\pi_{t-1} + \frac{\alpha_1+\alpha_2}{1-\gamma_c}x_t + \frac{u_t}{1-\gamma_c} \tag{A.30}$$

and the above equation will be used to compare the national inflation dynamics results directly from the national NKPC model.

Again, we don't indent here.

Appendix B

Appendix to Chapter 2

In this appendix section, I will briefly derive the variance covariance matrix of the weighted estimates in the implied aggregate model. To start with, for sector i, the sector specific NKPC regression takes the following form:

$$\pi_{it} = c_i + \gamma_f^{(i)} E_t(\pi_{i,t+1}) + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + u_{it}$$

and after replacing the rational expectation rates with realized inflation, the estimates of parameters will be obtained via

$$\pi_{it} = c_i + \gamma_f^{(i)} \pi_{i,t+1} + \gamma_b^{(i)} \pi_{i,t-1} + \beta^{(i)} ugap_t + \tilde{u}_{it}$$

where the parameter vector is defined as $\theta_i = [c_i, \gamma_f^i, \gamma_b^i, \beta^i]'$, and the unconditional moment is $E[g_{it}] = E[\tilde{u}_{it} Z_{it}] = 0$. Z_{it} is the instrument vector selected by some specific instrument selection procedure. Given the sample size T, the parameter estimate $\hat{\theta}_i$ should satisfy:

$$\sqrt{T}(\hat{\theta}_i - \theta_{i,0}) = -(D_i' W_i D_i)^{-1} D_i' W_i T^{-1/2} \sum_{t=1}^{T} g_{it}$$

Suppose the weighted parameter is $\theta_w = \sum_{i=1}^{N} \omega_i \theta_i$, and then the variance covariance matrix of the estimated θ_w is

$$Var(\theta_w) = Var(\sum_{i=1}^{N} \omega_i \theta_i)$$

Therefore, in order to get to know the variance covariance matrix of θ_w, we should know the covariance of any specific estimates θ_i and θ_j, weighted by their own weights ω_i and ω_j.

$$\begin{aligned} cov(\hat{\theta}_i, \hat{\theta}_j) &= E[(\hat{\theta}_i - \theta_{i,0})(\hat{\theta}_j - \theta_{j,0})'] \\ &= E[(D_i' W_i D_i)^{-1} D_i' W_i (\frac{1}{T} g_{it})(\frac{1}{T} g_{it})' W_i D_i (D_i' W_i D_i)^{-1}] \end{aligned}$$

The calculation of the covariance matrix of specific sector NKPC coefficients can be reduced to calculate the covariance of corresponding moment vectors. And the latter can be numerically achieved in the matlab.

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