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Three Essays in Empirical Macroeconomics

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Doctor of Philosophy

Economics

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Economics
2013.

Abstract

Three Essays in Empirical Macroeconomics

By Mzwandile Ginindza

This dissertation offers empirical analyses of three topics in macroeconomics. Firstly, it examines the short-run impact of common and idiosyncratic technology shocks on total hours worked in US Manufacturing. This is achieved via the use of industry factor-augmented structural vector autogressions (FASVAR). The findings suggest that hours worked increase in response to a common technology shock, yet they decline in response to idiosyncratic technology shocks. Secondly, the dissertation studies the dynamic impact of investment-specific technical changes on the skill composition of labor in US Manufacturing. Various structural VAR specifications, including one with long-run sign restrictions, are used to identify an investment-specific technology shock. The study finds that this shock tends to cause an initial increase in the demand for unskilled labor, which eventually declines after about 2 years. Essentially, after a short-term de-skilling effect, investment-specific technical changes become skill-biased in the long run. Lastly, the dissertation evaluates the effect of Inflation Targeting monetary policy on the inflation levels and inflation volatility in developed economies. This is achieved via the use of an Average Treatment Effects (ATE) approach, with a newly proposed matching tool, to control for selection bias among countries that adopted this policy. Since the ATE methodology normally studies effects at the mean, this study deploys non-parametric methods to extend the analysis to the entire distributions of inflation levels and volatility. The results suggest that Inflation Targeting helped its adopters in lowering inflation levels but not its volatility. The effect is shown to extend beyond the mean of inflation.

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1 Chapter 1

The Impact of Technology Shocks on Hours Worked at the Industry Level: An FASVAR Approach

Abstract

This paper offers an empirical analysis of the effect of technology shocks on hours worked at disaggregated levels. Rather than modeling productivity directly, I propose the decomposition of labor productivity growth into unobserved common, and industry-specific components from which technology shocks are extracted. This is achieved by means of a Factor Augmented Structural Vector Autoregression (FASVAR) approach originating in Bernanke, Boivin and Eliacsz (2002). The findings herein suggest that the response of hours worked is sensitive to which component of productivity growth experiences the shock. Furthermore, altering the specification of hours worked (between levels and first-differences), which is a contentious issue at aggregate level studies, does not affect the qualitative conclusions in this paper. A robustness check also reveals that the expected effect of controlling for inventory holdings gets subdued in the FASVAR environment.

1.1 Introduction

The past decade has seen a substantial increase in the amount of interest in the relationship between hours worked and changes in productivity. Standard Real Business Cycle (RBC) models had earlier conjectured a positive comovement between technology improvement, output and employment. The basis of this conjecture lies both in the upward sloping labor supply curve, and a rightward shift in the labor demand curve incited by a positive technology shock. The intuition is that it is beneficial for a firm to hire more workers when the marginal product of labor outweighs the cost, which is in the form of real wages. This concept was shown at least as early as in Burns and Mitchell (1946), and, later, in the seminal works of Kydland and Prescott (1982), and Long and Plosser (1983) to name a few. However, the empirical findings of Gali (1999) marked a pivotal point in the subject matter as he challenged the long-held RBC conjecture. Using a Structural Vector Autoregression (SVAR) with long-run restrictions on post-war US data, Gali found that hours worked, in the short-run, actually decline after a positive technology shock. He also uncovered that the contribution of technology shocks to the business cycle has become very minimal, a claim that seemingly put the valid existence of RBC models at risk. Gali's findings were later reproduced in Shea (1998), Francis and Ramey (2002), Francis and Ramey (2009), and Gali and Rabanal (2004) amongst others. Nevertheless, there is a sub-category of research that has recently reproduced the initial findings of RBC models. The most outstanding in this category is Christiano et al. (2003), and Christiano et al. (2004), who point out that the short-run impact of a technology shock on hours depends on how they are specified in a VAR model, which, in itself, relies on stationarity or unit root assumptions for hours. Unlike Gali and the other authors who found similar results, Christiano et al. (2003) advocate the use of level per-capita hours through which they produce an increase in hours after a positive technology shock. In an indirect attempt to find common ground, Pesavento and Rossi (2005) apply an agnostic methodology in which the researcher does not have to impose stationarity assumptions on hours worked. Using this approach, they find that hours decline after a positive technology shock but the decline is very short lived, especially in comparison to previous findings. Further in the direction of bridging the gap, Gospodinov et al. (2011) expand on the existence of a crucial low-frequency comovement between labor productivity and hours, which is handled differently in levels and in first-differences, thus explaining the inconsistencies in the implications of the two models. While the levels specification incorporates this comovement when computing impulse responses, the differenced specification suppresses it to zero. Gospodinov et al. (2011) uncover that removing the low frequency component and using long-run restrictions yield similar results for both the levels and differenced specifications of hours.

A large volume of work studying this topic, including the above listed, focuses on the national aggregate economy, yet substantial evidence has been presented on the heterogeneity of growth patterns at the sector level. For instance, Harberger (1998) presents an empirical demonstration of the diverse productivity patterns observed at the firm level in US data. He argues that a proper understanding of changes in aggregate productivity calls for capturing the patterns at the grassroot (firm) level. In a different, yet relevant, context, Foerster et al. (2008) uncover that variations in national Industrial Production can be explained by both aggregate and sector-specific variables. They profess that shocks to the latter fail to cancel out on aggregate, and that complementary sector-linkages may propagate sector-specific shocks throughout the economy thus generating aggregate variability. Specific to the relationship between technology shocks and employment, limited effort has been directed towards disaggregated analyses. Notable exceptions include Basu et al. (1998) and Basu et al. (2006), who use Solow residuals from 29 industries to formulate what they profess to be a purified aggregate technology series. Upon controlling for increasing returns to scale and input utilization, they find that technology improvements cause employment to decline in the short-run. Such findings are in total agreement with those made by Gali. Chang and Hong (2006) use a bivariate Structural VAR, adopting Gali's long-run restrictions, to investigate whether improvement in an industry's Total Factor Productivity (TFP) raises or lowers employment. Using data from 458 US manufacturing industries, they find vastly varying patterns of responses of hours across industries, but observe that more industries exhibit a positive short-run co-movement between hours worked and TFP shocks. Specifically, 133 industries show statistically significant increases in hours worked after a positive TFP shock, whereas only 25 industries show significant decreases in hours worked. Holly and Petrella (2012) build up on the work of Chang and Hong (2006) by controlling for inter-sectoral linkages[1] using a VAR with exogenous variables (VARX) that are weighted according to input-output tables. Restrictions for their VAR are obtained from a simplified multi-sector growth model. Their findings show that after controlling for sector linkages, a positive shock to labor productivity is expansionary with respect to hours worked.

In this paper, I closely review some recent publications on the impact of technology shocks on disaggregated hours, and proceed to make a methodological contribution to the analysis. The motivation behind this paper lies in the unresolved controversy surrounding the topic, and also on the observed shortage of relevant disaggregated studies, despite a growing movement to reconcile macroeconomic phenomena with micro-foundations. My argument is twofold; firstly, I conjecture that, at an industry level, labor productivity is driven by both idiosyncratic factors and factors common across all industries; secondly, I argue that an important determinant of the response of hours is the cross sectional scope of the technology shock i.e. whether the one time shock is experienced on a common factor or on an industry-specific factor of productivity. By means of a Factor Augmented Structural VAR (FASVAR) methodology, I estimate unobserved common and idiosyncratic factors that drive productivity growth across industries and use them in the empirical model, instead of productivity itself. Compared to a standard VAR, this approach incorporates more pertinent information into the model, hence allows the use of a large data set. Indeed I find that hours worked respond differently after a permanent shock to the common factor than they do after a similar shock to the idiosyncratic component.

[1] The existence and importance of inter-sectoral linkages has been shown in works such as Kim and Kim (2006), Horvath (1995), and Foerster et al. (2008) .

The remainder of the paper is as follows: in the next section I closely review selected work in the literature in order to set as a benchmark for findings herein. I introduce the general econometric framework in the third section, whereas data and specific details of the methodology are provided in section 4. The fifth section presents results from the FASVAR, and a discussion of my findings follows in section six, supplemented by a robustness check to investigate the role of inventory holdings in the response of hours worked. Section 7 provides a conclusion.

1.2 A Closer Literature Review

Among the works cited above, Chang and Hong (2006) conduct one of the most extensive disaggregated analyses of the topic at hand. As stated earlier, they utilize data on 458 4-digit level manufacturing industries categorized under the Standard Industrial Classification (SIC). This data covers the time period $1958 - 1996$. They further aggregate the data to both the 3-digit and 2-digit levels. Methodologically, they perform a bivariate SVAR, using long-run restrictions, to study the short-run response of hours worked to a positive TFP shock. They find that the number of positive short-run responses exceeds that of negative responses at all three industry-classification levels. For comparison, they also use labor productivity instead of TFP, and obtain more negative responses. However, they profess TFP to be the most natural measure to use since labor productivity reflects input mix and efficiency, and therefore conclude that technology shocks are pro-cyclical with respect to hours worked.

As a benchmark for my results, I adopt Chang and Hong's bivariate SVAR consisting of labor productivity and hours for all industries. While acknowledging their argument for the use of TFP, I gather that using labor productivity provides for better policy implications[2]. I utilize the same US manufacturing database but my variables for output and hours slightly differ, with justification, from Chang and Hong's. Firstly, while they use total worker

[2] Appendix A in Holly and Petrella (2012) presents a complete account on the use of labor productivity versus TFP.

hours I use production-worker hours. Dars and Gujarati (1972) asserts that production-worker wages in the short-run are considered variable costs whereas non-production worker wages are overhead or fixed costs. This implies that short-run employment of production-workers is directly related to output whereas that of non-production workers is only loosely so. Consequently, using production-worker hours is more fitting as it ensures a relatively greater short-run responsiveness of employment to productivity changes. Secondly, instead of gross output I use value-added output to compute labor productivity. This is because the database uses sales (value of shipments) as a proxy for output, and gross sales do not account for material purchases. As a result, an industry's large sales value could merely be reflective of high costs of intermediate inputs instead of actual internal production. The use of value-added output accounts for material (input) purchases and thus gives a more favorable account of labor productivity for the purpose of this paper.

In Table 13 I present the contemporaneous responses of hours to a one time permanent shock to labor productivity. The bold numbers indicate statistically significant responses whereas those in parentheses indicate total responses. Negative (Positive) denotes a contemporaneous reduction (increase) in hours, and No Impact refers to those impulse responses that were zero when rounded off to the fourth decimal point, and are taken to indicate no contemporaneous response in hours. I successfully replicate the qualitative findings of Chang and Hong i.e. that responses vary across industries but the overall majority of them are negative. Two general points of deviation stand out; one is that in my replication there are relatively more positive responses than in the original work, and the numerical differences between positive and negative statistically significant responses at each level are smaller than in the original work. In particular, I find that:

1) At all disaggregation levels more positive responses are teased out than in Chang and Hong. This holds for both statistically significant responses and total responses.

2) At the 4-digit level (the most disaggregated level) there are almost as many statistically

significant positive responses as there are negative ones.

3) At the 2-digit level (the least disaggregated level), statistically significant positive responses actually outnumber negative ones.

Table 1 – *Contemporaneous Responses of Production Hours to a Labor Productivity Shock*

	Personal Ginindza (2012)			Chang and Hong (2006)	
Disaggregation Level	**Negative**	**Positive**	**No Impact**	**Negative**	**Positive**
4-digit	**28** (300)	**27** (131)	27	**174** (351)	**17** (107)
3-digit	**25** (63)	**17** (41)	36	**60** (115)	**6** (25)
2-digit	**3** (10)	**4** (7)	3	**9** (18)	**0** (2)

Notes: Responses are statistically significant at the 90% confidence interval. Figures in parentheses are total responses.

The use of value-added output is arguably instrumental in the emergence of more positive responses compared to Chang and Hong. As pointed out in Holly and Petrella (2012), intermediate inputs play a role in relating productivity changes and employment. The intuition is that productivity changes at input-producing industries will likely affect the final-use industries as well, and this is reflected in the response of hours. Holly and Petrella (2012) effectively account for this by using input-output tables which provide dollar values of each industry's input and output uses. Using the same data, their exercise yields mostly positive responses of hours worked to a technology shock. While value-added output on its own does not achieve the same control as input-output tables, it is a step in that direction hence the increased positive responses in my replicated results.

Owing to the inter-industry linkages in production processes, I argue that an industry's own labor productivity change is not sufficient in explaining that particular industry's short-run behavior of production hours. Instead, more relevant cross-sectional information ought to be incorporated in the study, which is what this paper seeks to do. As can be imagined, there are numerous variables that would have to be included for a satisfactory model amid the limited capability of structural models in handling many variables. My proposed solution is the decomposition of labor productivity growth into unobserved common and idiosyncratic factors that drive it across industries. The idea is that there is useful information, of varying scope, contained in labor productivity that is not readily observable to the econometrician. Through the proposed decomposition, the model is enriched without encountering the dimensionality challenges that prevail in standard VAR models. To my knowledge, no recent publication has taken this particular direction in the context of relating technology shocks and employment. A closely related concept can be found in Wang and Wen (2007) who use the purified technology series from Basu et al. (2006) to formulate sector-specific and aggregate shocks. The purified series is obtained from the residuals of sector production functions under perfect competition, constant returns to scale, and no changes in labor and capital utilization. Specifically, the shocks are obtained as dz_i in the following function:

$$dy_i = \gamma_i(dx_i + du_i) + dz_i, \tag{1}$$

where dy_i refers to sector i's output change, dx_i is input change, du_i refers to unobserved changes in input utilization, and γ_i is the arbitrary degree of the function's homogeneity in total inputs. Aggregate shocks (dz) are computed as the weighted sum of dz_i across i. Wang and Wen then regress dz_i on both its lag and the aggregate technology shock, dz, to get sector-specific shocks. For 29 sectors, they study the average response of output and selected inputs to both aggregate and sector-specific technology shocks. They report that the difference lies mainly on the horizon i.e. aggregate shocks are contractionary in the short-run whereas sector-specific technology shocks are contractionary both in the short-run and long-run.

However, it can be noted that the process described above does not ensure orthogonality between the aggregate and sector-specific shocks. Also, the aggregate shock, as calculated there, is merely a summation of the sector-specific shocks, it does not necessarily represent unique information. My proposed use of factor analysis addresses these two concerns as it produces unique common and idiosyncratic factors under orthogonality restrictions. Applications of factor analysis in macroeconomic contexts are not uncommon. For instance, Foerster et al. (2008) use factor analysis to study the variation in the Industrial Production index. They demonstrate that common factors account for most of the variations in the US IP index. Also, Kose et al. (2003) use factor analysis to study global, regional and country specific business cycle patterns. This paper joins the recently growing trend of researchers that merge factor analysis with Vector Autoregressions, an idea pioneered in Stock and Watson (2005). Details of the framework are provided in the following section.

1.3 General Econometric Framework

The method applied in this paper originates in Bernanke et al. (2005) (henceforth BBE) in their study of the effects of monetary policy. In an attempt to capture the large volume of information utilized by policy makers, BBE estimate unobserved common factors of 120 macroeconomic variables, and use these in a VAR analysis. By studying the impulse responses of up to 5 factors, they are able to infer the effect of a monetary policy shock on the 120 macroeconomic variables. In a similar sense, this paper seeks to incorporate additional cross-sectional information into a standard structural VAR model to explain the relationship between technology shocks and employment. Unlike BBE who extract their factors from different variables, the factors here are extracted from the same variable (labor productivity growth) but across a panel of 458 industries. This enables the capturing of unobserved forces driving productivity across all the industries that may be relevant in influencing the short-run behavior of production hours. By incorporating common factors in the model, this paper avoids treating the industries as completely separate and independent entities, a limitation that can be pointed out in Chang and Hong's work. Going beyond the application in BBE, I further extract the components driving productivity growth which are specific to each industry (idiosyncratic factors), and study their impact on production hours after a technology shock. Stock and Watson (2005) demonstrated in a Monte Carlo experiment that a model that merges factor analysis with VAR outperforms a standard VAR. Originally coined FAVAR in BBE, I refer to the methodology here as a Factor Augmented Structural VAR (FASVAR), and what follows below are details of its specification.

For each industry i at time t, let ΔY_{it} denote the growth of labor productivity, and similarly let Δn_{it} denote the growth of hours worked. The debate surrounding the specification of hours in levels or first-differences will be discussed in later sections, for now we use first-differences for comparability with Chang and Hong (2006). Also, for both simplicity and compliance with preexisting literature, we assume an economy that is exposed to only two types of shocks, namely technology and non-technology shocks.[3] Conventionally, technology shocks are associated with the supply side, and are often extracted from either labor productivity or TFP. In this context, the technology shocks are interpreted as the permanent change in the unobserved common factor of labor productivity growth, and, later, in the idiosyncratic component of labor productivity growth. The non-technology shocks stem from demand-side elements. In estimating the FASVAR model I use the two-step approach suggested in Stock and Watson (2005) and adopted by BBE. In the first step, I utilize asymptotic principal components to estimate the common factors.

Fundamentally, this estimation procedure entails expressing a given N x T series X_t as follows:

$$X_t = \Lambda F_t + e_t, \tag{2}$$

[3]Interpreting the specific non-technology shocks is beyond the scope of this paper, as is the detailed interpretation of the common and idiosyncratic factors of productivity growth.

where F_t denotes a vector of $k < N$ common factors driving X_t, Λ refers to a vector of factor loadings, and e_t refers to an N x T vector of idiosyncratic components. The factor loadings represent the degree to which each of the series in X_t correlates to F_t. The vector F_t itself cannot be directly estimated, but what is estimable is the space that it spans i.e. one can estimate an orthogonal vector whose entries span the same space spanned by entries of F_t. The estimation enforces the restriction that $E(F_t e_t) = 0$, that is, the common factors and the idiosyncratic components should be mutually orthogonal. Stock and Watson (1998) developed a nonparametric method to estimate the factors, and Ng and Bai (2002) show that, given a large enough N, the factor estimates are indeed efficient. This method involves minimizing the following least squares criterion:

$$V_{N,T}(\hat{F}_t, \hat{\Lambda}) = (NT)^{-1} \sum_{t=1}^{T} (X_t - \Lambda F_t)^2 \tag{3}$$

It is found that (3) is consistently minimized by the principal components of X_t, which are obtained from weighted eigenvalues of the T x T covariance matrix of X_t. Since the factors are unobserved, an important question becomes how many factors does one extract? To determine the appropriate quantity of factors I apply a commonly used criterion proposed in Ng and Bai (2002), which is also based on the above mentioned nonparametric estimation approach of Stock and Watson. The criterion is as follows:

$$IC_2(k) = ln\left(V_{N,T}(\hat{F}_{(k)}, \hat{\Lambda}_{(k)})\right) + k\left(\frac{N+T}{NT}\right) ln(min\{N,T\}), \tag{4}$$

where $V_{N,T}(\hat{F}_{(k)}, \hat{\Lambda}_{(k)})$ is as defined in (3) for a k factor model. After the factor estimates are obtained, they are then incorporated with hours in a bivariate Structural VAR in the second step.

1.4 Empirical Implementation

1.4.1 Data

The data I use in the empirical application is jointly prepared by the National Bureau of Economic Research (NBER) and the Census Bureau's Center of Economic Studies (CES). It covers a total of 458 manufacturing industries in the United States over the period 1958-1996. The Asbestos industry is excluded as it only has observations up to 1993. The industries are classified based on the 1987 Standard Industrial Classification (SIC) system, and the raw data is disaggregated to the 4-digit level, which is the most disaggregated level under SIC. The SIC was discontinued in 1997 and replaced by the North American Industrial Classification (NAIC) which accommodates more sub-industries but covers a relatively shorter time period. Among the key differences between the two is that the SIC groups industries by the output type while the NAIC groups them by the production processes. Labor productivity is computed as the log difference between real value-added output and production hours. Value added output is given as the shipment-value net the value of intermediate inputs. The growth of labor productivity is computed as the first-difference of labor productivity, $\Delta Y_{it} = Y_{it} - Y_{it-1}$, where $\{i = 1, ...N\}$ is the number of industries, and $\{t = 1, ...T\}$ denotes time. Similarly, Δn_{it} denotes the log difference of production hours worked. Additional variables are the logs of end-of-year total inventory holdings, and total real capital stock. Using the criterion of Ng and Bai (2002), I determine that productivity growth at the 4-digit level is driven by a single common factor, F_t (i.e. $k = 1$). To investigate the effect of aggregation, the analysis is performed at three SIC disaggregation levels. I start off with the original 458 4-digit industries, and then aggregate to the 3-digit level. This is achieved by grouping industries by their first two classification digits, and then summing their values. For instance, the following 4-digit industries 2011, 2013 and 2015 form the 201 3-digit industry upon aggregation. This process yields 140 industries, which are further aggregated, based on the first digit, to produce 20 2-digit level industries. The summation is done before any computation or transformation of variables is undertaken. Additionally, data on raw material and work-in-process inventory holdings is obtained from the Bureau of Economic Analysis (BEA), and it is only available at the 2-digit industry level.

1.4.2 Estimation

The joint dynamics of $(F_t, \Delta n_{it})$ are expressed via the following VAR;

$$\begin{bmatrix} F_t \\ \Delta n_{it} \end{bmatrix} = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix} \begin{bmatrix} F_{t-1} \\ \Delta n_{it-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ w_{it} \end{bmatrix}, \tag{5}$$

and the proposed factor decomposition of labor productivity growth is as follows:

$$\Delta Y_{it} = \Lambda_i F_t + \Lambda_{in} \Delta n_{it} + e_{it}. \tag{6}$$

The factor, F_t, enters the model in levels since it is extracted from a stationary panel, ΔY_{it}, and Ng and Bai (2004) demonstrate that factors of a stationary panel are themselves stationary. The subscript, i, on the factor loadings allows each industry to respond differently to changes in the common and idiosyncratic factors. The decomposition in 6 is based on the neoclassical multi-sector production function

$$X_{it} = A_t z_{it} K_{it}^{\alpha} N_{it}^{1-\alpha}, \tag{7}$$

where X_{it}, K_{it}, and N_{it} denote output, capital stock, and labor input per sector, respectively. A_t and z_{it} are common and sector-specific technologies. Herein, I assume that there are two types of industries; final producers and intermediate-good industries. The final producers utilize, as intermediate input, production from the latter. For simplicity, it is further assumed that intermediate-goods sectors produce their own inputs.

Equations (5) and (6) constitute the FASVAR. The last two terms on the right hand side of 6 constitute the idiosyncratic component of ΔY_{it}, which is composed of an observed component (hours) and an unobserved component (e_{it}). Capital stock is omitted in the model application since it is commonly assumed to be constant in the short-run. As a robustness check, I included it as an additional observed idiosyncratic component in 6, and it did not alter the qualitative findings.

1.4.3 Step One: Factor Identification

Following BBE, in the first step of the methodology I do not exploit the fact that Δn_{it} is observable. I rely on the demonstration in Ng and Bai (2002), and Stock and Watson (2002) that the method of principal components, given a large enough N, consistently recovers the space spanned by both observed and unobserved factors. Consequently, I extract the factor estimate, $\hat{F}_t$, as the largest principal component of a demeaned and standardized ΔY_t that minimizes (3). This yields the following

$$\Delta Y_{it} = \Lambda_i \hat{F}_t + \xi_{it}, \tag{8}$$

where the term ξ_{it} encompasses the space spanned by both hours worked and the unobserved idiosyncratic component e_{it}. This component is recovered by running the regression

$$\xi_{it} = \hat{\lambda}_{in} \Delta n_{it} + e_{it}. \tag{9}$$

1.4.4 Step Two: SVAR Identification

In step-two I estimate the VAR in (5), where I replace F_t by $\hat{F}_t$, the factor-estimate obtained in step-one. I identify the structural shocks by using the Cholesky decomposition to impose long-run restrictions, as originally proposed by Blanchard and Quah (1989), and famously adopted in Gali (1999). According to these restrictions, hours can be freely affected by both technology and non-technology shocks across the model's horizon. However, non-technology shocks are restricted from affecting productivity in the long-run. The restrictions imply that what I interpret as a technology shock is the permanent disturbance to the factors that drive productivity growth. Let Δx_{it} denote the vector of $\{\hat{F}_t, \Delta n_{it}\}$, and let the two residual terms be expressed in the vector $\epsilon_{it} = \{\eta_t, w_{it}\}$. The moving average form of (5) can be expressed as

$$\Delta x_{it} = C(L)\epsilon_{it}, \tag{10}$$

where C is constructed from the VAR coefficients using the canonical algorithm over the VAR horizon m as follows:

$$C_m = \sum_{j=1}^{m} C_{m-j}\Phi_j, \tag{11}$$

with $C_0 = I$.

For some matrix Z, the structural form is derived as:

$$\Delta x_{it} = D(L)\epsilon^*_{it}, \tag{12}$$

where $\epsilon^*_{it} = Z^{-1}\epsilon_{it}$ is the vector of structural shocks and $D(L) = Z^{-1}C(L)$ are the impulse responses, both of which are of primary interest. For the ease of notation, let $R = Z^{-1}$, and assume $RR' = \sum_\epsilon$, where $\sum_\epsilon = \epsilon\epsilon'$ is the covariance matrix of ϵ_{it}. I estimate R such that

$$D(1) = C(1)R, \tag{13}$$

where $D(1)$ and $C(1)$ are the cumulative sums of matrices D and C. With the above assumptions, I get that

$$D(1)D'(1) = C(1)\Sigma_{\epsilon}C'(1). \tag{14}$$

Applying the lower triangular Cholesky decomposition yields the matrix

$$D(1) = Chol[C(1)\Sigma_{\epsilon}C'(1)], \tag{15}$$

from which I finally obtain R using (13):

$$R = C(1)^{-1}D(1) \tag{16}$$

1.5 Empirical Results

In Table 2 below, I present results obtained from running the FASVAR model across all three disaggregation levels namely: 4-digit level (maximum disaggregation), 3-digit level (intermediate disaggregation) and 2-digit level (minimum disaggregation). At each level, the second step (the SVAR) is carried out per industry hence I obtain as many impulse responses as there are industries in that particular level. As stated in the previous section, a large N ensures a consistent estimation of the unobserved factors hence I extract the common factor, $\hat{F}_t$, at the four-digit level where I have the largest panel. However, even when I extract a distinct common factor at each disaggregation level, I obtain factors that look very similar, as can be clearly seen in Figure 1. Such similarity substantiates the consistency of my estimated factor. The top panel in Table 2 reports the short-run responses of hours after a one time technology shock to $\hat{F}_t$. The last two columns report the number of industries that either decreased or increased hours contemporaneously after the shock, as a percentage of total industries in each disaggregation level. The percentages in bold refer to statistically significant responses, while those in parentheses denote total increases or decreases for each disaggregation level. All results are based on the Impulse Response Functions (IRFs) generated from the empirical model. Statistical significance is at the 90% confidence interval, which I obtain via a bootstrap of the residuals. The second column states the specification of hours, and the third column indicates which factor of prudctivity is exposed to the shock. IRFs for the 2-digit level industries are included in Figures 2-5, whereas those for the 3-digit and 4-digit levels are intentionally witheld to economize page space[4].

The results obtained are strikingly suggestive. Using hours in first-differences as in Basu et al., Gali, and Chang and Hong, I find that a positive permanent shock to the common factor of productivity is expansionary for the majority of manufacturing industries. This result holds across all three disaggregation levels, and seemingly gets enforced as I aggregate the data. Specifically, at the 4-digit, 3-digit and 2-digit levels I observe, respectively, that

[4]They are, however, available and obtainable from the author upon request.

52%, 76%, and 85% of the industries had statistically significant increases in hours after the shock, whereas there were only 0.8%, 0%, and 0% statistically significant decreases. Recall that the benchmark model in section 1.2 produced mixed but largely negative responses after the shock, a result that complies with preexisting literature where hours are similarly specified. The current findings, therefore, validate my proposed decomposition as they suggest that cross-sectional labor productivity contains hidden information that renders shocks to productivity partialy pro-cyclical. Figure 2 shows the impulse response functions for the 2-digit level industries after a shock to $\hat{F}_t$. It can be seen that all the industries's responses peak within 3 years, and 60% peak on impact before dropping towards a new and higher equilibrium.

Table 2 – *Impulse Responses of Hours to a Common Factor Shock (as a % of total sectors in each disaggregation level)*

Disaggregation Level	**Hours**	**Shock Origin**	**Decreases**	**Increases**
4-digit	Differences	F_t	**0.8** (7) %	**52** (90) %
3-digit	Differences	F_t	**0** (4) %	**76** (91) %
2-digit	Differences	F_t	**0** (0) %	**85** (100) %

Responses of Hours to an Idiosyncratic Shock in Percentages

Disaggregation Level	**Hours**	**Shock Origin**	**Decreases**	**Increases**
4-digit	Differences	Idiosyncratic	**8** (36) %	**7** (35) %
3-digit	Differences	Idiosyncratic	**16** (50) %	**4** (26) %
2-digit	Differences	Idiosyncratic	**20** (60) %	**0** (35) %

Notes: Percentages in bold refer to statistically significant responses, while those in parentheses refer to total responses.

In my application of the FASVAR approach, a meaningful extraction and use of the idiosyncratic components of the data is possible. This is not always the case since in most relevant applications, e.g. BBE, the data consists of different macroeconomic time series where the idiosyncratic components are often interpreted as measurement errors. In my case, however, these refer to factors of productivity growth that are industry-specific, a relatively broader concept than measurement errors. I am thus motivated to investigate the effect, on hours, of applying a permanent shock to the idiosyncratic components. This entails running step-two of the model where F_t is now replaced by the idiosyncratic component in equation (5). The results are presented in the bottom panel of Table 2. The most notable observation is that the results now appear diluted. The responses are more evenly spread than in the previous case, yet a clear pattern can still be detected. At all disaggregation levels, the percentage of industries that decrease hours exceeds that of industries with increased hours, both overall and in terms of statistical significance. While these results contrast the findings in the top panel of Table 2, they are more in agreement with findings from previous work where hours are modeled in differences. Chang and Hong also come to a similar conclusion when using labor productivity growth as a source of their technology shock. These results prompt the suggestion that perhaps a standard VAR model of labor productivity largely identifies shocks to the idiosyncratic component, disregarding the common factor. The orthogonality restrictions imposed on F_t and e_{it} in step-one ensure that in my analysis I obtain a truly unique effect from each component. This could explain the contrasting effects I get as opposed to Wang and Wen (2007) whose correlated aggregate and sector-specific shocks are both contractionary but differ across the horizon. My findings could have non-trivial policy implications because federal, state and district central planners might have different employment expectations when making decisions on funding productivity innovations.

1.5.1 Level Specification of Hours

A major source of disagreement on the effect of technology shocks on hours lies in the specification of hours in structural models, particularly at the national aggregate level. A consensus is yet to be reached as to whether hours should be entered in differences or in levels. Papers that have used the first-difference specification tend to find technology shocks to be contractionary with respect to hours worked. At the national aggregate level such papers include Gali (1999), Shea (1998), and Francis and Ramey (2009) among others. The argument in these works is that hours follow long cycles that distort conditional dynamics of the level specification. On the other hand, there are arguments for entering hours in levels. In particular, Christiano et al. (2003) and Christiano et al. (2004) (henceforth CEV) make findings that are in line with the initial RBC conclusions when they use per capita hours in levels, and further point out misspecification concerns in models with differenced hours. However, in a survey paper Whelan (2004) compares the specifications in Gali and CEV and concludes that only the former is robust to different VAR specifications, different data used, and different measures of productivity. Furthermore, Eroglu and Hofer (2007) declare that the results obtained using levels are mostly driven by structural breaks in US data.

When they remove subsample means from the data they find that both levels and differences produce similar conclusions as in Gali (1999). At the disaggregated level papers such as Basu et al. (2006), Holly and Petrella (2012) and Chang and Hong (2006) enter hours in first-differences. Chang and Hong base their choice on unit root tests that show US disaggregated data as being stationary in first-differences. However, Gospodinov et al. (2011) clarify that unit root tests are ineffective in determining the appropriate specification as they often exhibit a bias towards stationarity of differenced hours. This is mainly due to their handling of an observed low frequency comovement in VAR coefficients linking hours and productivity. Unlike the level specification, first-differences tend to suppress this comovement to zero thus influencing tests to report stationarity. Canova and Michelacci (2010) make the argument that while level hours have long cycles, first-differencing emphasizes high frequency hours variability. They argue that this could magnify the measurement error problem, especially since the difference system's 90% tunnel is larger than that of levels. Thus they conclude that both levels and differences are likely to be misspecified. In this paper I choose not to pursue the issue further, instead I choose to present results for both specifications to test the robustness of my methodology.

When I enter hours in levels, all the conclusions, reported earlier, still hold but become less obvious. Generally, the responses are diluted and more evenly spread between increases and decreases compared to the previous case of differenced hours. In particular, after a permanent shock to F_t, there are more increases, than decreases, in hours at the 2-digit and 3-digit levels. At the 4-digit level, 52% of industries decreased hours after the shock. However, focusing on statistically-significant responses, I get more increases at all levels. Consequently, the pro-cyclicality of F_t with respect to hours is sustained.

A shock to the idiosyncratic components yields similar conclusion as in the differenced specification. Responses vary across industries and disaggregation levels, but a majority of them are decreases, both nominally and in terms of statistical significance. The levels specification seems to generally tease out more positive responses in hours after a technology shock, but not enough to reverse conclusions otherwise made under the differences specification. The robustness of my results is important as it enables my work to fit in with either side of the specification debate in the literature.

Table 3 – *Impulse Responses of Hours to an F_t Shock in Percentages (Level Specification)*

Disaggregation Level	Hours	Shock Origin	Decreases	Increases
4-digit	Levels	F_t	**4** (52) %	**14** (38) %
3-digit	Levels	F_t	**8** (45) %	**34** (48) %
2-digit	Levels	F_t	**0** (30) %	**45** (70) %

Responses of Hours (in Levels) to an Idiosyncratic Shock in Percentages

Disaggregation Level	Hours	Shock Origin	Decreases	Increases
4-digit	Levels	Idiosyncratic	**17** (44) %	**7** (33) %
3-digit	Levels	Idiosyncratic	**27** (47) %	**7** (33) %
2-digit	Levels	Idiosyncratic	**35** (75) %	**10** (25) %

Notes: Figures in bold refer to statistically significant responses, while those in parentheses refer to total responses.

1.6 Discussion

The findings presented above are consistent with economic intuition. Since my econometric specification does not account for price-stickiness, I provide an interpretation of the findings based on a classical, flexible-price framework. By virtue of extracting a cross-sectionally common factor of productivity growth, I introduce an inter-industry link between the production processes. Recall that the multi-sector growth model, introduced in section 4, assumed two types of producers, namely intermediate-good producers, and final producers. An analysis across-types provides for more dynamics than within-types. Essentially, an improvement in productivity across all industries (i.e. an increase in A_t in equation 7), leads to an overall increase in production to capitalize on the decreased marginal cost. This induces a downward pressure on prices, including the prices of intermediate inputs. Intermediate-good producers will increase production, additionally, to meet the increased demand from final producers. This overall quest for increased output potentially drives the short-run increase in hours worked, and this could be in the form of overtime hours or increased employment. On the other hand, if the productivity improvement is industry-specific, then a set of coincidences is required for production and prices to change. After an industry-specific shock to final-good producer, J, its price (production) will only lower (increase) if there is a decline in marginal costs(including the cost of inputs). This calls for the relevant input suppliers to also experience shocks of their own. In the absence of such a coincidence, producer J will need less labor to sustain current production, hence idle workers will be laid off or work reduced hours. This translates to the observed short-run decline in hours in the data. Similarly, a shock to an intermediate-good producer will only alter output and prices if the relevant final-good producers experience a shock of their own. A different sort of coincidence, involving inventory holdings, is discussed below.

1.6.1 The Role of Inventories: A Robustness Check

In this section I seek to find out if a firm's ability to hold inventories would alter the contemporaneous response of hours in my empirical setting. Inventories are generally used by firms for production-smoothing, and stock-out avoidance. After storage cost considerations, a firm can afford to increase production after a productivity improvement, if it can keep the additional output as inventories. This could facilitate an increase in employment after a technology shock. At the national aggregate level, changes in inventory investment have been shown to impact on an economy's gross domestic product (GDP), and are documented as substantial contributors to business cycle dynamics[5]. A commonly held conjecture, pioneered in papers by McConnell (2000), Blanchard and Simon (2001), and Kahn et al. (2000), states that inventories played a major role in the US Great Moderation, a period of steady decline in output volatility observed in the mid 1980s. In an unpublished paper, Chang et al. (2009) (henceforth CHS) propose a theoretical model that introduces inventories to the standard Taylor (1980)-type model of staggered prices. Their model predicts that firms with inventory holdings increase employment after a technology shock, even under sticky prices. [6] Using US manufacturing data, they produce largely positive responses of hours after a positive technology shock, confirming their model's prediction. They further cite

[5] See, for instance, Blinder (1981) and Hornstein (1998)

[6] Gali (1999) uses the standard sticky price intuition to explain the negative response of hours he obtained.

demand elasticity, and product durability as additional contributing factors to the positive responses of hours worked.

I am keen on exploring the role, if any, of inventories in the response of hours worked to a technology shock in an FASVAR setting. In effect, can inventories eradicate the negative responses observed in earlier sections, particularly after an idiosyncratic shock? If inventory holdings can overcome the contractionary effect of sticky prices, as theoretically shown in CHS, then one would expect them to easily yield positive responses under flexible prices. However, I posit that an industry's own ability to hold inventories is, alone, not sufficient in determining the true influence of inventories on response of hours. Due to the interconnectedness in production processes, inventory holdings in other relevant industries should also matter. Consequently, I argue that because of linkages in industrial production processes, the impact of inventories should depend on which component of productivity is shocked. In the case of a common shock to productivity, this point is trivial and inventories can be expected to yield more positive responses. However, for inventories to incite an expansionary effect after an idiosyncratic shock, coincidental inventory holdings among final and intermediate producers could be required. Consider a positive idiosyncratic shock to intermediate-good producer, G, that holds inventories. If the corresponding final producer(s) also hold inventories, hours in G are likely to increase. However, if the final-producer(s) do not hold inventories, market limitations will likely hinder G from increasing production.

I investigate this notion via FASVAR, where step-two becomes a tri-variate SVAR consisting of a factor of productivity, hours worked, and real inventory holdings. This step is represented as follows:

$$\begin{bmatrix} F_t \\ \Delta n_{it} \\ \Delta m_{it} \end{bmatrix} = \begin{bmatrix} \Phi_{11} & \Phi_{12} & \Phi_{13} \\ \Phi_{21} & \Phi_{22} & \Phi_{23} \\ \Phi_{31} & \Phi_{32} & \Phi_{33} \end{bmatrix} \begin{bmatrix} F_{t-1} \\ \Delta n_{it-1} \\ \Delta m_{it-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ w_{it} \\ v_{it} \end{bmatrix}, \tag{17}$$

where Δm_{it} denotes the log-difference of real total inventories. I only report findings for the differenced specification of hours for direct comparison with CHS. I use both the common and idiosyncratic factors of productivity in the SVAR. The idiosyncratic factor, obtained in step-one, is further purified into $\tilde{e}_{it}$ by including real inventories as an additional observable in regression 9 as follows:

$$\tilde{\xi}_{it} = \hat{\lambda}_{in}\Delta n_{it} + \hat{\lambda}_{im}\Delta m_{it} + \tilde{e}_{it}. \tag{18}$$

I maintain the same assumption that the economy is only faced with two kinds of shocks, namely a technology shock, η_t, and non-technology shocks, (w_{it} and v_{it}). I augment the long-run restrictions by assuming that the factor of productivity used is not affected by either hours or inventories in the long-run, whereas inventories do not affect hours in the long-run. Both hours and inventories are permanently affected by the productivity factor. Thus a Choleski decomposition, as used earlier, is sufficient to attain these restrictions. The results are reported in Table 4, and they show that, a positive shock to F_t expectedly yields positive hours' responses in a large majority of industries, and this gets strengthened by aggregation. When F_t is replaced by an idiosyncratic factor, I get more evenly spread responses. At the 4-digit level, the majority of total responses are negative, whereas at the 2-digit level the majority are positive responses. At the 3-digit level, I get an equal quantity of total positive and negative responses. However, focusing on statistical significance, positive responses exceed negative responses at all levels, although the percentage differences are not overwhelmingly large. These results are in line with the argument that the role of inventories is dependent on the scope of the shock, as judged by the component of productivity affected. Inventory holdings are not as successful, in producing an expansionary effect, after an idiosyncratic shock as they are with a common shock. As a result, the conclusions reported in section 5 remain unchanged by the inclusion of inventories.

1.6.2 Output vs Input Inventories

The literature on inventory investment can be generally classified into two categories. One focuses on the use of final-good inventories for the purpose of stock-out-avoidance, and it has received abundant attention. The other, which had mostly been neglected, incorporates the stage-of-fabrication linkages within and between firms where input inventories are utilized for production-smoothing. Input inventories, conventionally defined as raw materials and work-in-process products, arise whenever there is a gap between the delivery and use of inputs. They had been neglected in earlier models because their importance was largely observable in durable goods, and earlier models commonly excluded such goods[7]. However, the significance of input inventories in production and business dynamics has been pointed out in recent work. Humphreys et al. (2001), for instance, show that input inventories are larger and fluctuate more than finished-good inventories in US manufacturing. Findings in Herrera and Pesavento (2005) show that at the disaggregated level, input and output inventories contributed differently to the reduction in output volatility during the Great Moderation. Tsoukalas (2005) states that since the usage of input materials is a factor of production, decisions on production-smoothing and output-inventory are inherently related to input-inventory decisions. Eroglu and Hofer (2011) investigate the contribution of the different inventory types to a firm's financial performance, and find that Raw Material inventories contribute the most compared to Work-in-Process and Final Good inventories. Meanwhile, Lieberman and Demeester (1999) uncover a negative correlation between productivity growth and input inventories, particularly Work-in-Process (WIP). Their key argument is that reducing WIP exposes production problems on the shop floor, enabling

[7] See Blinder and Maccini (1991) for a summary of earlier literature.

them to be attended to hence boosting productivity. In turn, an increase in productivity leads to a further reduction in the need for WIP.

From these publications arises the motivation to disintegrate my inventory variable into its different components, and investigate whether they have different effects on the relationship between hours and productivity. The US manufacturing data on input inventories is only available for 2-digit level industries. I run the FASVAR second step, with total inventories replaced, in turns, by Final Goods (FG), Work-in-Process (WIP) and Raw Material (RM) inventories. I present the results on the last three rows of each panel in Table 4. Regarding a shock to F_t, none of the inventory components yields negative hour-responses. Meanwhile, an idiosyncratic shock produces some interesting variations. Firstly, input inventories (RM and WIP) produce more total industries with increased hours than those with decreased hours. WIP yields 60% while RM yield 55%. Meanwhile, output-inventories exhibit a more expansionary effect, with 60% total industies with increased hours. Secondly, while all inventory components produce more statistically sginifcant increases, WIP has the least percentage. Based on statistical responses, the overall conclusions in this paper do not change after decomposing inventories. However, one can note a slight contractionary effect from input-inventories, especially WIP. This could be associated with the arsserted negative relationship between productivity and WIP, which would imply that an accumulation of WIP tends to counter the initial improvement in productivity, aiding the contractionary effect of the shock.

Table 4 – *Hours' Responses to a Common Factor Shock in Percentages (Tri-variate SVAR Results)*

Sector Level	Shock Origin	Decreases	Increases
4-digit	F_t	**1.3** (16) %	**42** (84) %
3-digit	F_t	**0.7** (10) %	**68** (90) %
2-digit	F_t	**0** (0) %	**80** (100) %
FG	F_t	0(0) %	**90**(100) %
WIP	F_t	0(0)%	**75**(100)%
RM	F_t	0(0)%	**85**(100)%

Hours' Responses to an Idiosyncratic Shock in Percentages

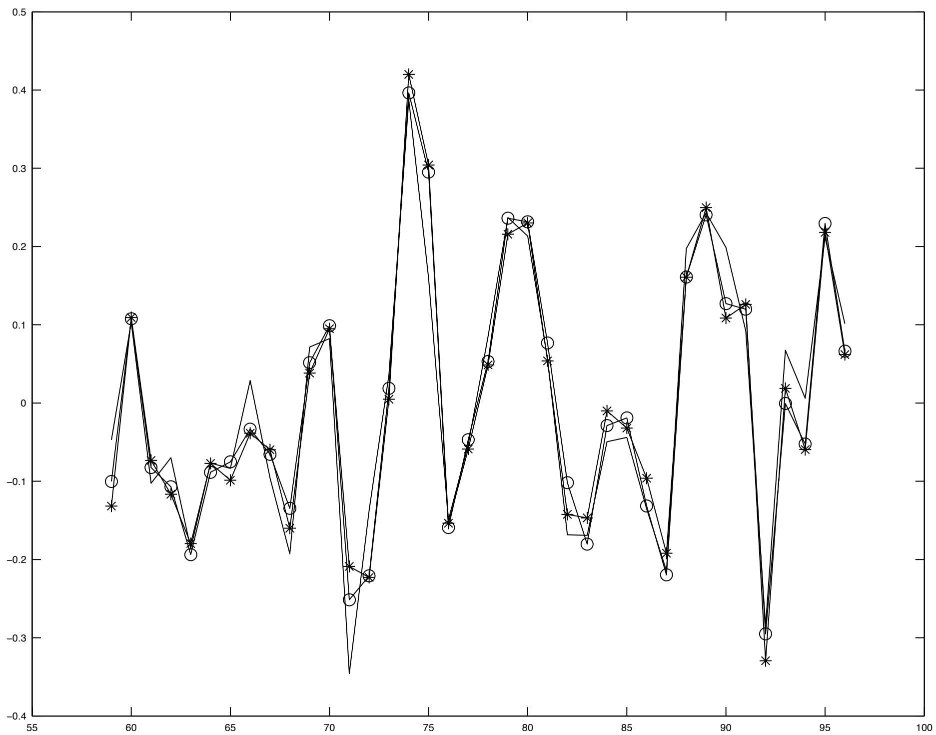
Sector Level	Shock Origin	Decreases	Increases
4-digit	Idiosyncratic	**15** (51) %	**12** (49) %
3-digit	Idiosyncratic	**17** (50) %	**16** (50) %
2-digit	Idiosyncratic	**20** (45) %	**15** (55) %
FG	Idiosyncratic	**10** (40)%	**30** (60)%
WIP	Idiosyncratic	**10** (60)%	**25** (40)%
RM	Idiosyncratic	**10** (55)%	**35** (45)%

Hours are in first-differences. Bold figures denote 90% statistical significance, while those in parentheses refer to total responses.

1.7 Conclusion

The issue of the response of hours after a technology shock has not been fully resolved. Much emphasis has been placed on the specification of hours, particularly at the average economy level. In this paper, I undertake an empirical study of the short-run relationship between technology shocks and hours worked at disaggregated levels. I use a Factor Augmented Structural Vector Autoregression to decompose labor productivity into unobserved common and idiosyncratic factors across manufacturing industries in the United States, and study the response patterns. This decomposition appears to render productivity partially pro-cyclical and partially anti-cyclical, with respect to hours worked, depending on which of its components gets exposed to the shock. A technology shock to the common factor incites an increase in hours worked in a majority of industries, whereas an industry-specific shock appears more contractionary. Importantly, these conclusions do not seem to depend on the specification of hours, an outcome that should facilitate a fair reception of my work from either side of the contrasting schools of thought. Additionally, the inclusion of inventory holdings in my empirical model, whether combined or divided into input and output components, attest to the significance of accounting for the scope of a technology shock. Important policy implications of my findings hinge, in part, on the perceived direction of advances in production processes. If industries are advancing towards homogenized production technologies, then more emphasis should be laid on the common factors driving productivity. However, if industrial production processes strive towards increased specialization, then more attention ought to be paid to idiosyncratic elements. The findings herein further highlights the potential risk of disregarding useful information when carrying out this analysis at the national aggregate level. In that case the researcher neither sees nor chooses the source or scope of a technology shock, and lets that decision rest on the model. Potential extensions to this work include exploring possibilities for economic interpretation of the common and idiosyncratic factors of productivity extracted. Also, it would be of great interest to investigate the effect of non-neutral technology changes such as investment specific technology shocks.

Figure 1 – *Graphs of Common Factors Extracted at Each Disaggregation Level*



Stars= F_t at 4-digit level, Circles= F_t at 3-digit level, Solid= F_t at 2-digit levels

Figure 2 – *Two-digit level: IRFs of First-differenced Hours to a One Time Shock to F_t*

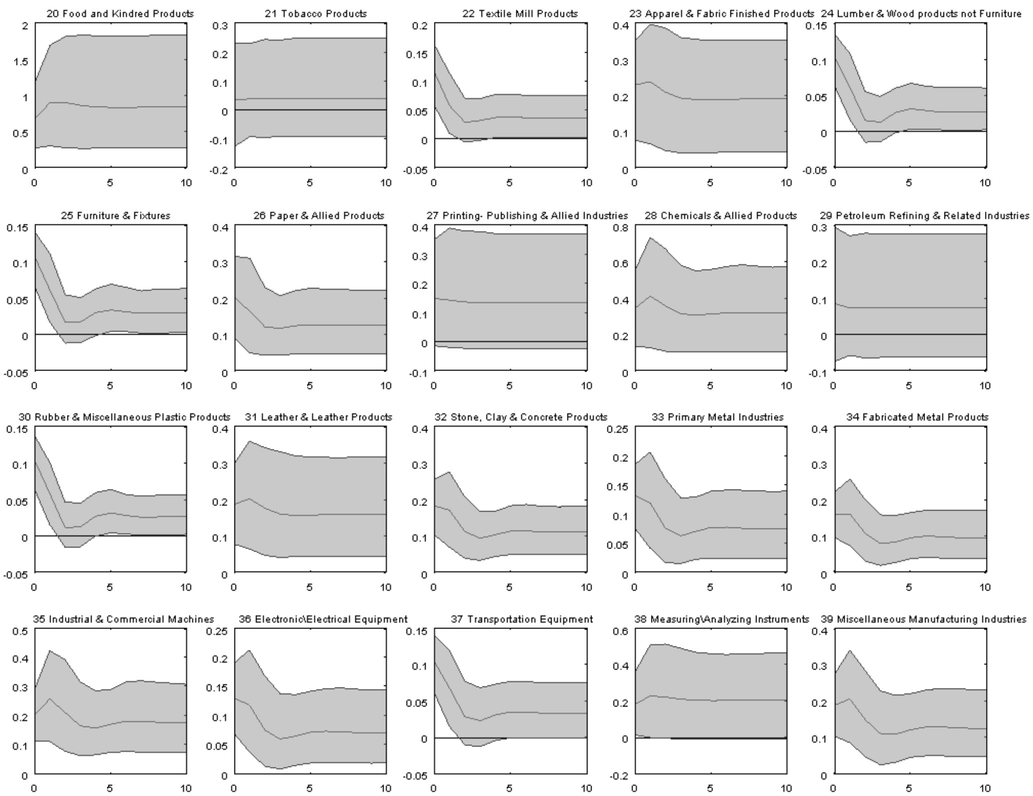


Figure 3 – *Two-digit level: IRFs of First-Differenced Hours to a One Time Shock to the Idiosyncratic Components*

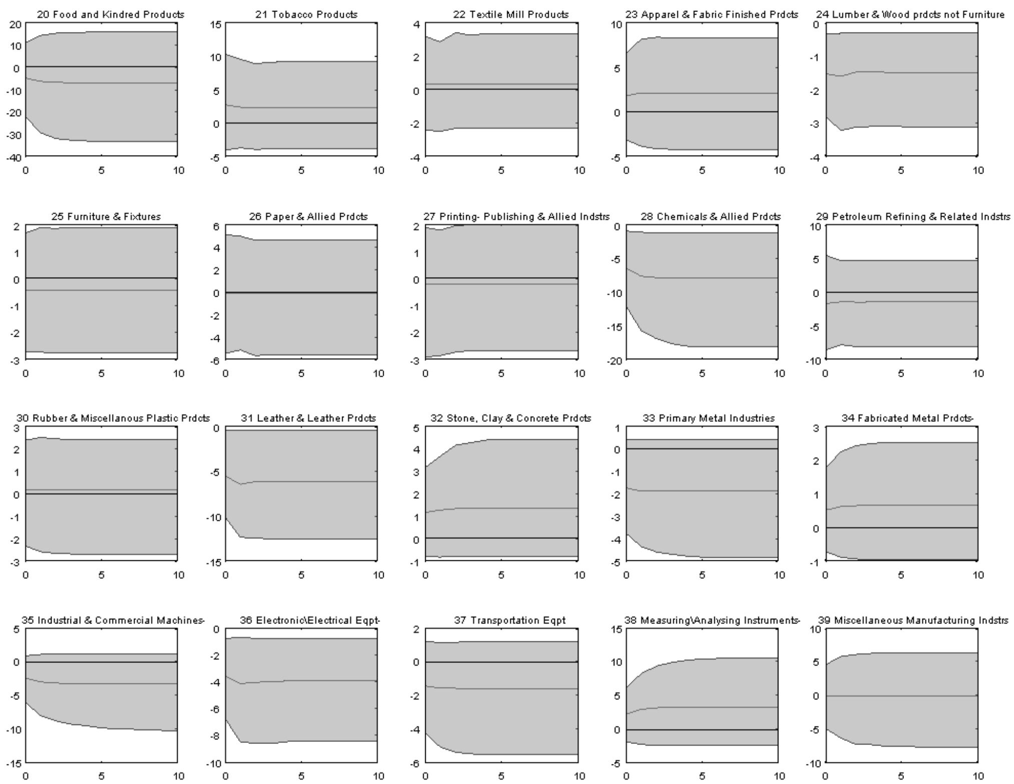


Figure 4 – *Two-digit level: IRFs of hours (levels) to a One Time Technology Shock to* F_t

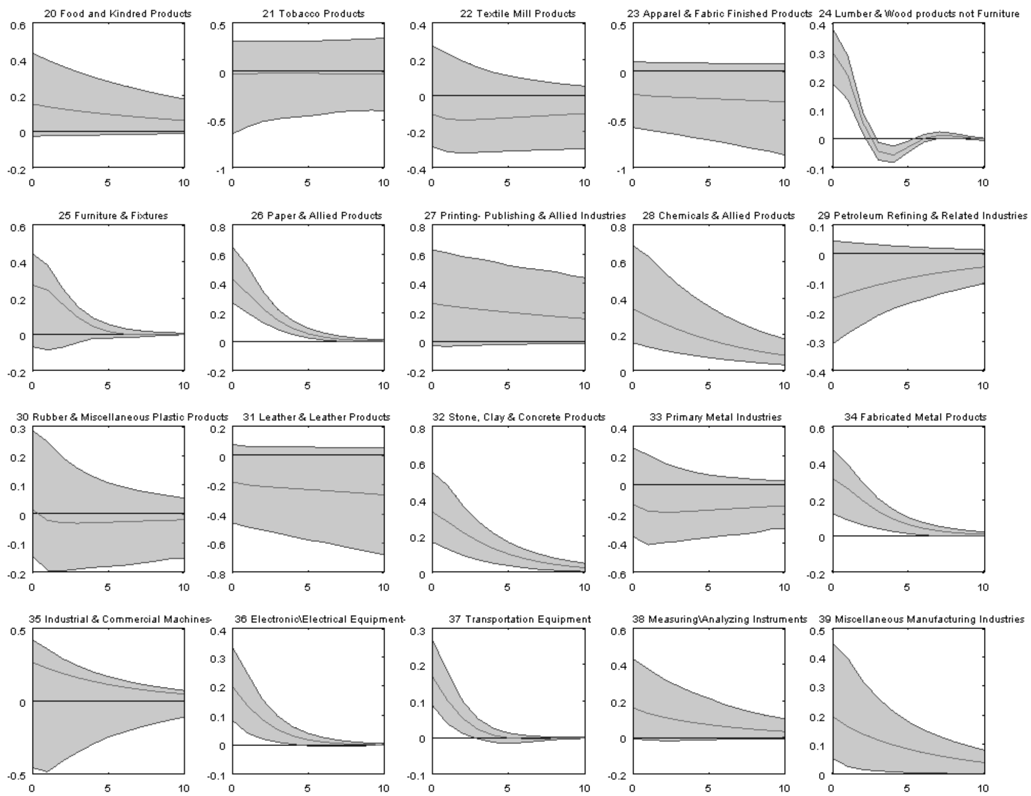


Figure 5 – *Two-digit level: IRFs of hours (levels) to One Time Technology Shocks to Idiosyncratic Components*

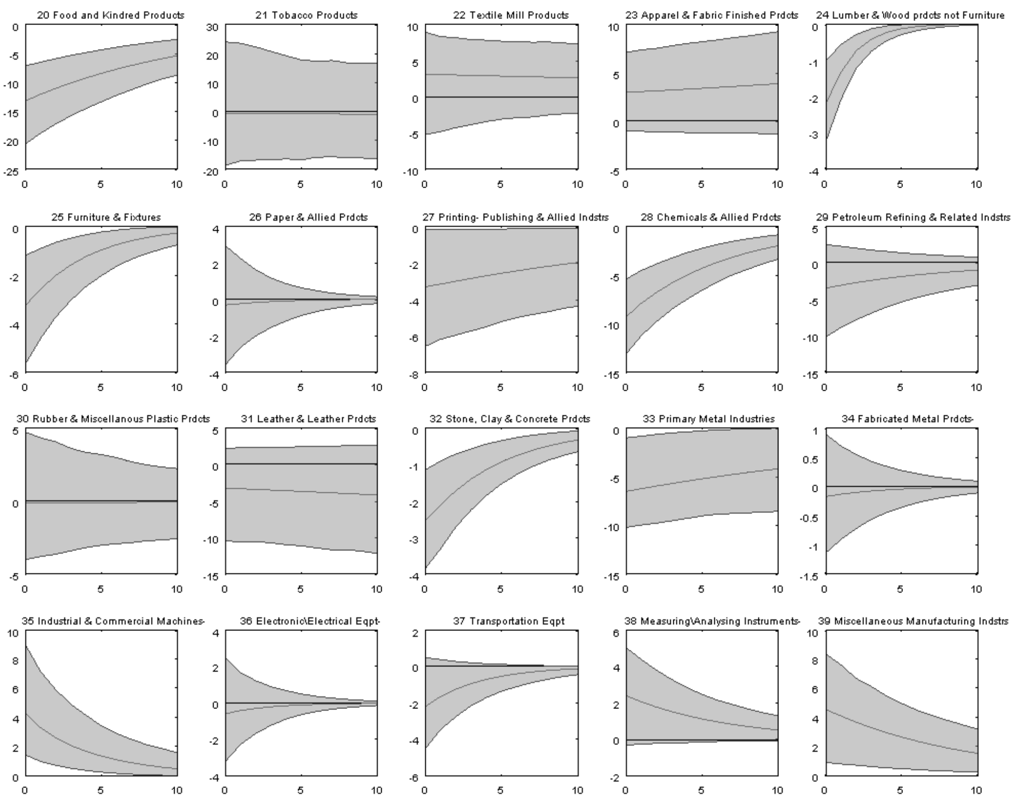


Table 5 – *List of 2-digit Sectors Classified Under SIC*

SIC CODE	Sector Description
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel and Fabric Finished Products
24	Lumber and Wood products not Furniture
25	Furniture and Fixtures
26	Paper and Allied Products
27	Printing- Publishing and Allied Industries
28	Chemicals and Allied Products
29	Petroleum Refining and Related Industries
30	Rubber and Miscellaneous Plastic Products
31	Leather and Leather Products
32	Stone, Clay and Concrete Products
33	Primary Metal Industries
34	Fabricated Metal Products
35	Industrial and Commercial Machines
36	Electronic and Electrical Equipment
37	Transportation Equipment
38	Measuring and Analyzing Instruments
39	Miscellaneous Manufacturing Industries

Table 6 – *List of 3-digit Sectors Classified Under SIC*

201 Meat Products	238 Miscellaneous Apparel and Accessories
202 Dairy Products	282 Plastic Materials and Synthetic Prdcts-
203 Canned Preserved F and V	239 Miscellaneous Fabricated Textiles
204 Grain Mill Products	241 Logging
205 Bakery Products	242 Sawmills and Planing Mills
206 Sugar and Confectionery Prdcts	243 Millwork and Structural Wood Members
207 Fats and Oils	244 Wood Containers
208 Beverages	245 Wood Bldgs and Mobile Homes
209 Miscellaneous Food prep-	249 Miscellanoues Wood Prdcts
211 Cigarettes	252 Office Furniture
212 Cigars	251 Household Furniture
213 Chewing and Smoking Tobacco and Snuff	253 Public Bldg and Furniture
214 Tobacco Stemming and Redrying	254 Partitions Office and Store Fixtures
221 Broadwoven Fabric Mills, Cotton	259 Miscellaneous Furniture and Fixtures
222 B.W Fabric Mills- fiber and Silk	261 Pulp Mills
223 B.W Fabric Mills, wool	262 Paper Mills
224 B.W Smallwares Mills Combined	263 Paperboard Mills
225 Knitting Mills	265 Paperboard Containers and Boxes
226 Dyeing and Finishing Textiles	267 Converted Paper and paperboard prdtcs
227 Carpets and Rugs	271 Newspapers:Publishing and Printing
228 Yarn and Thread Mills	272 Periodicals: Publ and Printing
229 Miscellaneous Textile Goods	273 Books
231 Men and boys' suits Coats	274 Miscellaneous Publishing
232 Men-boys' Furnishings Work gear	275 Commercial Printing
233 Women's Outerwear	276 Manifold Business Forms
234 Women-Children's Undergarments	277 Greeting Cards
235 Hats Caps and Millinery	278 Blankbooks Looseleaf Binders etc.
236 Girls-Children's Outerwear	279 Service Printing indtrs
237 Fur Goods	281 Industrial Inorganic Chemicals

282 Plastic Materials and Synthetic Prdcts-
283 Drugs
284Cleaning Preps and Toiletries-
285 Paints Enamels etc.
286 Industrial Organic Chemicals
287 Agric Chemicals
289 Miscellaneous Chem Prdcts
291 Petroleum Refining
295 Asphalt Paving and Roofing-
299 Miscellaneous Coal and Petrol Prdcts
301 Tires and Inner Tubes
302 Rubber and Plastic Footwear
305 Gaskets and Sealing Devices-
306 Fabricated Runner Prdcts-
308 Miscellaneous Platic Prdcts
311 Leather Tanning and Finishing
313 Boot and Shoe Cut Stock-
314 Footwear not Rubber
315 Leather Gloves and Mittens and Handling Machinery-
316 Luggage
317 Handbags and Personal Leather Goods
319 Other Leather Goods
321 Flat Glass
322 Pressed-Blown Glassware
323 Prdcts from Purchased Glass
324 Cement and Hydraulic
325 Structural Clay Prdcts
326 Pottery Prcts
327 Concrete and Plaster Prdcts
328 Cut Stone and Stone Prdcts
329 Asbestos and Nonmetal Prdcts
367 Electronic Componets and Accessories
369 Misc Electrical Machinery Eqpt
371 Motor Vehicle and Eqpt
372 Aircraft and Parts
373 Ship Boat Bldg and Repairs
374 Railroad Eqpt
375 Motorcycles Bikes and Parts
376 Guided Missiles and Space-
379 Misc Transportaion Eqpt
381 Search Navigation etc Eqpt-
384 Surgical Medical Instruments
331 Steel Works Furnaces etc.
332 Iron and Steel Foundries
333 Primary Smelting N.F. Metals
334 Sec N.F. Smelting
335 Extruding N.F. Metals
336 Nonferrous Foundries
339 Miscellaneous Prim Metal Prdcts
341 Metal Cans and shipping Containers
342 Cutlery and General Hardware-
343 Heating Eqpt-
344 Fabricated Struct. Metal Prdcts
345 Screw Machine Prdcts-
346 Metal Forgings and Stampings
347 Coating and Allied Services
348 Ordnance and Accessories-
349 Miscellaneous Fabricated Metal Prdcts
351 Engines and Turbines
352 Farm and Garden Machine and Eqpmt.
353 Construction
354 Metalworking Machinery
355 Special Industry Machinery-
356 General Industry Machinery
357 Computer and Office Eqpt.
358 Refrigeration and Service Ind Machinery
359 Misc. Ind and Commercial Machinery
361 Electric Transmission and Distr Eqpmt.
362 Electrical Ind. Apparatus
363 Household Appliances
364 Electric Lighting and Wiring Eqpmt.
365 Household Audio Video Eqpmt.
366 Communications Eqpt
385 Opthalmic Goods
386 Photographic Eqpmt.
387 Watches and Clockwork Devices
391 Jewelry Silverware Plated Ware
393 Musical Instruments
394 Toys Games Athletic Goods
395 Pens and Artists' Materials
396 Costume Jewelry not Pr. Metal
399 Misc Manufacturing Industries
382 Lab Apparatus etc.

2 Chapter 2

The Dynamic Effect of Investment Specific Technical Change on Labor Composition in US Manufacturing

Abstract

In this paper, I use a series of structural VAR specifications to explore the dynamic effects of investment-specific technological changes (ISTC) on the skill composition of labor. I focus on the US Manufacturing sector for the period 1958-2009, where evidence of a compositional shift in labor demand is substantial. Using non-production and production workers to proxy for skilled and unskilled labor, I find that the characteristic effects of ISTC exhibit important dynamism. While in the short-run ISTC fail to explain observed data patterns, they tend to do so well in longer horizons. This suggests that the capital-skill complementarity in US Manufacturing comes into effect with some lags. A shock identified from the skill premium via a sign restriction VAR only showed partial characteristics of being the "complete" skill-biased technology shock.

2.1 Introduction

Since the controversial findings in Gali (1999), numerous papers have analyzed the decline in hours-worked after a one-time positive technology shock, particularly in post-war US data. A contractionary neutral technology shock negates initial findings by Real Business Cycle models, and also contradicts the positive co-movement between productivity improvements and employment that is observed in the data. These two points have led to the argument that the role of technology shocks in driving short-run economic fluctuations has greatly diminished. Any validity in this argument would suggest that other types of shocks matter more in steering the business cycle. As a result, research focus in this topic is steadily shifting towards the identification of such shocks, particularly non-neutral technology shocks[8]. Recently, notable attention has been given to the role of investment-specific technological changes (ISTC) in driving the business cycle. These refer to improvements either in the production process, or in the quality of newly produced capital goods. The effect of these improvements is reflected in the declining relative price of investment goods to consumption goods. In the US this relative price has been declining over the past three decades. Among the first to highlight the importance of ISTC were Greenwood and Krusell (2000) who reported the substantial contribution (60%) of ISTC in explaining output growth in the US economy. Numerous researchers have expanded these findings, and noteworthy among them are Cummins and Violante (2002), Fisher (2006), Ho (2008) and Basu et al. (2010). The last three are of special interest in this paper. Fisher (2006) and Basu et al. (2010) argue that the seemingly diminished role of technology shocks stems from the narrow definition that is often used when identifying a technology shock[9]. They proceed to show that accounting for other types of technology shocks overturns the argument regarding the diminished role. Fisher (2006) identifies an investment-specific technology (IST) shock from the relative price of investment in a multi-variate VAR that also includes national aggregate labor productivity, total hours, and other exogenous variables. To account

[8]These can be generally viewed as disturbances that improve the productivity of a selected subset of inputs or sectors.

[9]Gali (1999) and subsequent papers identify a technology shock as the disturbance that causes a permanent change to labor productivity or Total Factor Productivity (TFP).

for policy and regulatory changes associated with the Great Moderation, Fisher splits his data into two subsamples, 1955:I-1979:III and 1982:III-2000:IV. With the first one, he finds that hours decline after each technology shock, both when there is one and two technology shock(s) identified. However, in the second subsample, hours respond positively, with a hump shape, to an IST shock whereas their response to a neutral technology shock is insignificant. Basu et al. (2010) set up a multi-sectoral environment consisting of consumption goods sectors and investment goods sectors. They then compile what they profess to be "purified" technology shocks from the production functions of these sectors, and find that technology shocks identified in the investment goods sectors cause hours to decline, whereas consumption-goods technology shocks are expansionary. Finally, Ho (2008) studies the effect of ISTC and Total Factor Productivity (TFP) on labor composition in US manufacturing using a fixed effects regression analysis. Upon finding a positive coefficient for ISTC and a negative one for TFP, he concludes that ISTC yield an increase in the demand for skilled labor while TFP has the opposite effect.

In this paper, I use a series of SVAR model specifications to study the dynamic effects of IST shock on labor composition in US Manufacturing for the period 1958-2009 [10]. This period provides evidence that a compositional shift in labor demand occurred. In particular, both the supply and wages for skilled labor exhibit an upward trend during this period, while the opposite holds for unskilled labor. Pinning down the forces behind this compositional demand shift is both of research interest, and also important in explaining the decline in total hours after a neutral technology shock as observed in recent literature. For the latter, it could be the case that the decline in total hours is a reflection of a decline in unskilled labor due to the shift in demand for skill. In this case, modeling a neutral technology shock alone would not suffice. Instead, a technology that exhibits some bias based on skill ought to be identified. To this end, I empirically investigate whether an IST shock could be the main driving force behind the compositional demand shift. I achieve this by analyzing the dynamic responses of labor composition to a positive IST shock both

[10] In the data section, I offer arguments as to why the US Manufacturing sector is of great interest and importance for this analysis.

in a single-technology and multiple-technology model specifications. This is because an IST shock could have one of two contrasting effects on the composition of labor. On one hand, an IST shock can be skill-biased as it can improve the productivity of skilled labor. On the other hand, it can reduce the need for skill, in which case it is considered to be de-skilling. Studies of IST shock on aggregate total hours have already been done hence the contribution of this paper is investigating the dynamic impact on labor composition, and doing so for the manufacturing sector. This study, simultaneously, enables me to determine whether capital-skill complementarity holds for US Manufacturing. According to my knowledge, no publication has performed this exercise for the manufacturing sector. The closest work is done by Ho (2008), but his methodology falls short of capturing the dynamism of the effect of IST shock. The use of the SVAR methodology facilitates this and also ensures a proper identification of the shocks. As a robustness check, I utilize a sign restriction VAR in an attempt to identify a skill-biased technology shock.

The remainder of the paper is as follows: subsection 2.2 provides details of the data used in this study. In subsection 2.3, I specify single-technology SVAR models to analyze the effect of an IST shock both on total manufacturing labor, and on the skill composition of labor. Subsections 2.4, 2.5 proceed to multiple-technology specifications where I investigate the supply side effects of an IST shock in the labor market, and then investigate the demand side via the inclusion of the relative wages for skilled and unskilled labor. In subsection 2.6, as a robustness check, I use a VAR with sign restrictions in an attempt to identify a skill-biased shock from the skill premium, and in 8 I conclude.

2.2 Data

This study is limited to the US Manufacturing Sector for the following reasons. Firstly, Manufacturing has long been a crucial sector and a cornerstone of the US economy. It has demonstrated sustained productivity growth and is shown by the National Association of Manufacturing(NAM) as having the highest multiplier effect out of all sectors[11]. Secondly,

[11] For every \$1 spent in manufacturing another \$1.48 is added to the economy.

technology shocks have been shown to have different effects on variables at disaggregated levels, and a substantial case has been made that productivity is better measured in manufacturing than in other sectors[12]. Thirdly, the manufacturing database provides variables that proxy better for skilled and unskilled labor compared to other sectors and, arguably, to the variables used for aggregate studies. Related work done using national aggregate data relies on formal education as a classification for skill i.e. only a worker with a college degree (or a high school diploma in some cases) is considered skilled. Such classification only observes skill level on the first day of work and ignores skill obtained via experience. This presents a potential bias as a seasoned uneducated worker who is promoted to a skill-requiring position is still regarded as unskilled. With the manufacturing data, one can classify skill based on the actual job a worker does regardless of how they got there. Lastly, using Manufacturing data facilitates a comparison of findings in other relevant papers that have used the same database to study technological changes and employment, and these include Chang and Hong (2006), Ho (2008), Holly and Petrella (2012), and Basu et al. (2010). The data is annual and it comes from the NBER-CES Manufacturing Industry Database, which is jointly prepared by the National Bureau of Economic Research, and the Center for Economic Studies. The database has recently been updated, an exercise that has resulted to eight more years of observations being added to it. While it formerly had data up to 1997, the database, as of March 2013, now consists of US manufacturing industries for the period 1958-2009. It is available in two versions based on the classifications of industries; one uses the 1987 Standard Industrial Classification (SIC) system while another use the North American Industrial Classification (NAIC). For this paper I utilize the former, which contains 459 manufacturing industries at the most disaggregated level (4-digit level). To obtain data that is representative of the manufacturing sector as a whole, I aggregate the raw data into 20 two-digit level industries, and from there I calculate manufacturing aggregate variables. In doing so, I leave out eight industries at the 4-digit level as they each have at least nine missing observations due to the recent update. These industries are Asbestos Products, Logging, Newspaper: publishing and printing, Periodicals: publishing and print-

[12] Ngai and Samaniego (2009) and Kahn and Lim (1998).

ing, Books: publishing and printing, Miscellaneous Publishing, Greeting Cards, and Boat Building and Repairing. The database contains, among others, data on each industry's output, capital stock, total number of workers per industry, total number of hours worked by production workers, and their relevant wages. To obtain non-production and hence total hours worked, I follow convention in assuming that non-production workers work 2000 hours per year. Therefore, non-production hours are obtained from the product of non-production workers and 2000 hours. However, since workers are expressed in thousands while hours are in millions, it suffices to multiply by 2 rather than 2000. The database also contains industry-specific price indexes including a price index for investment products. In compiling the relative price of investment, I use the deflator for personal consumption of non-durable goods compiled by the Federal Reserve Bank of St. Louis (FRBSL), chain-weighted with NIPA(National Income and Product Accounts)-supplied weights. This index is preferred to the manufacturing-specific deflator for shipments which does not differentiate between consumption and other goods. For the investment index, I use both the manufacturing specific index, and the FRBSL-provided investment index. The latter is more preferable as it is broader, covering equipment and software as well.

2.3 A Single-Technology Empirical Specification

2.3.1 Investment Specific Technology Shocks and Total Hours

The non-trivial role of IST shocks in the business cycle has recently attracted significant research interest. The intuition behind these shocks, as described in Greenwood and Krusell (2000), lies in the assumption that a given economy has two sectors, one that produces consumption goods and another that produces investment goods (new capital). A change in the technology for producing consumption goods is viewed as a Hicks-neutral technological change, whereas productivity improvements in the investment goods sector are interpreted as investment-specific technological changes. Since there are only two sectors assumed, an IST shock refers to improvements in the production of efficiency units of investment goods, relative to their consumption counterparts. Depending on calculation methods, it can also embody improvements in the quality of new capital. The importance of $ISTC$ in driving economic growth was highlighted in Greenwood and Krusell (2000), who concluded that they contribute about 60% of economic growth in the US. Additionally, studies of their impact on hours has produced slightly mixed results. For instance, while Basu et al. (2010) find IST shocks to be contractionary to hours, Fisher (2006) finds them expansionary for the two decades post 1980. In the period prior to that, he finds IST shocks to be contractionary as well. Fisher's study was performed at the national aggregate level, whilst Basu et al. (2010) focused on industries but did not apply the VAR methodology. For a smooth transition from the existing literature into this paper, I start by investigating the dynamic effect of an IST shock on total hours for the manufacturing sector in a bivariate SVAR model. Theoretically, we could assume a simplified two factor production function in which firms only utilize capital-augmenting technology. For aggregate manufacturing, the production funtion would be as follows;

$$Y_t = (K_t A^k)^\theta N_t^{1-\theta}, \tag{19}$$

where Y_t, K_t, and N_t respectively denote output, equipment capital, and total labor at time t. Input shares are determined from the value θ. The parameter A_t^k is taken here to represent-investment specific technology.

2.3.2 Estimation

Following Fisher (2006), I identify an IST shock as the only source of permanent disturbance to the relative price of investment (for brevity, I shall refer to it simply as the relative price)[13]. Accordingly, I denote the endogenous variables in the model as $\Delta x_t = [\Delta Q_t, \Delta H_t]$, where ΔQ_t is the first log-difference of the relative price, and ΔH_t denotes the first log-difference of total manufacturing hours worked. The structural form is as follows:

$$B_0 \Delta x_t = B(L)\Delta x_{t-1} + e_t, \tag{20}$$

[13]In the estimation, I use the reciprocal of this price, $Q_t = \frac{P_t^c}{P_t^i}$. This is done simply for the ease of thinking in terms of increases in variables after positive self-originating disturbances.

where L is a lag polynomial operator, and in compliance with pre-existing literature, I select a single lag for the application herein. The matrix B is a square coefficient matrix, and B_0 is symmetric with ones on the diagonal. For estimation purposes, equation 20 is converted to its reduced form,

$$\Delta x_t = a + A(L)\Delta x_{t-1} + u_t, \tag{21}$$

where a is a vector of constants, $A(L) = B_0^{-1}B(L)$, and similarly, $u_t = B_0^{-1}e_t$. Of ultimate interest are the structural shocks, e_t, which can be identified from u_t, given an estimate of B_0. To this end, I impose long-run restrictions on the relationship between the model's endogenous variables. Essentially, under this approach, disturbances to hours (interpreted as non-technology shocks) are restricted from affecting the relative price in the long run. These non-technology shocks are assumed to originate from demand side factors, and their exact economic interpretation is beyond the scope of this paper. As a result, the relative price is only affected permanently by disturbances to itself. It is these permanent disturbances to the relative price that will be interpreted as the IST shock. On the other hand, hours are assumed to be permanently affected by both IST and non-technology shocks, hence no restriction is placed on their long run responses. To achieve these restrictions, a lower triangular structure is imposed on the cumulative structural response matrix.

Figure 6 presents the impulse responses to one standard deviation shocks from the model. The solid lines represent the point estimate impulse responses, and the dotted lines are 65% confidence intervals obtained via a bootstrap on the reduced form residuals. The figure shows that the IST shock identified in the model is contractionary with respect to total hours in US Manufacturing. Hours are shown to decline on impact, and permanently remain below the initial equilibrium. The contemporaneous decline in hours is in agreement with the results in Basu et al (2010) and the first sample of Fisher (2006). Furthermore, in comparison to the impact of a neutral technology shock (NTS) on hours, the impact responses are similar, yet after a NTS hours recover to levels above initial equilibrium in the long run. I show the responses to a NTS in figure 7, where the NTS is identified from labor productivity using similar identification restrictions as described above. Moreover, the relative price increases after an IST shock as investment goods become cheaper relative to consumption goods. Afte a non-technology shock, the relative price is shown to contemporaneously decrease but this response lacks statistically insignificance.

2.3.3 Labor Composition

In this section, I proceed to the primary focus of this paper, which is to study the effect of an IST shock on the skill composition of manufacturing labor. This analysis is of special interest partly because an IST shock can have two contrasting effects on the skill composition of labor. On one hand, it can improve the productivity or efficiency of skilled labor. Berman and Griliches (1969) observed this phenomenon and formalized it as the capital-skill complementarity hypothesis. It states that new capital and skilled labor are complements rather than substitutes. Caselli (1999) builds up on this notion and describes such shocks as skill-biased innovations. His view is based on the cost of adopting new innovations, and if such costs are lower for skilled workers then the innovation is skill-biased. As a result, the hypothesis asserts that new capital is more likely to be assigned to skilled workers, and that an increase in capital should increase (decrease) the demand for skilled (unskilled) labor[14]. On the other hand, it could also be that capital innovations may replace the need for skill. If the adoption costs for a new capital innovation are lower for unskilled workers, then the IST shock would be considered de-skilling and the demand for skilled labor will not increase. From this empirical analysis, I will be able to determine which one of these two ways defines the effect that the identified IST shock had on the skill composition in the chosen sample.

Further motivation for focusing on labor composition lies both in pre-existing literature, and in current evidence from the data showing a skill compositional shift in US Manufac-

[14]For recent discussions, see Greenwood and Yorukoglu (1997), Caselli (1999), Krusell et al. (2000), and Lindquist (2005).

turing, suggestive of a shift in labor demand patterns. The sample period in this paper coincides with an era of great technical innovations in the US, particularly between 1958 and 1982 where key advancements regarding computer usage occurred[15]. The tendency of firms to alter the proportion of skilled workers relative to unskilled workers, especially after the introduction of computers, is well documented[16]. Since unskilled workers generally outnumber their skilled counterparts, particularly in the manufacturing sector, a shift away from the former could yield a decline in total labor input, as observed in models studying the response of hours to neutral technology shocks. Given that skilled labor employment would be increasing, an observed decline in total labor input requires a careful deliberation by researchers and policy makers. Berman et al. (1994) provide evidence for a compositional shift in manufacturing for the 1980s in a data analysis exercise.

In figure 8, I present similar evidence, graphically, for the overall period of 1958-2009. The figure displays log averages for three labor variables, workers, hours, and wages for across 459 US Manufacturing industries over time. The graphs on the right panel are for non-production labor relative to manufacturing totals. Similarly, the left panel graphs are for production labor relative to manufacturing totals. Non-production workers undertake administrative, managerial, supervisory, marketing, research, and other skill-requiring duties, whereas production workers perform assembling, packaging, warehousing, janitorial and other duties up to the supervisory level. Consequently, these two variables are usable as good proxies for skilled and unskilled labor, respectively. Their attractiveness as proxies partly lies in the fact that they account for skill acquired via experience, rather than formal education. This avoids the potential underestimation of skilled labor, and hence a biased report on the resultant skill composition shifts. The graphs on the right panel in figure 8 exhibit an increasing trend in all the three variables for skilled manufacturing labor, whereas all three variables for unskilled manufacturing labor have been steadily decreasing.

[15]Examples of such innovations include the development of UNIVAC computers, Intel computers, floppy disks, FORTRAN programming language, Ethernet computer networking, IBM's first consumer computer and PC, and Microsoft Operating Systems with spreadsheet and word processor softwares.

[16]See Goldin and Katz (1998), Kahn and Lim (1998) and references therein for details.

Two tasks emerge from these patterns; the first task is to determine empirically whether this compositional shift is due to demand or supply forces, and secondly, whether an IST shock can explain these patterns, which would simultaneously, determine if capital-skill complementarity holds. Demand shifts would entail firms increasing demand for highly skilled workers as production processes get sophisticated due to new capital innovations. Regarding supply-side forces, it could be argued that post-war stability enabled workers to pursue career ambitions, improve their skills via education and other forms of training hence the overall labor force quality has improved. A mere look at the data seem to suggest a demand shift. This is because skilled labor hours are shown to increase together with the relevant wages. A supply-side force would require that wages for skilled labor be driven down in response to the increase in the supply of skilled workers. An empirical analysis of the impact of an IST shock on labor composition could simultaneously perform both tasks. I begin with a bivariate SVAR, as in the preceding section, and then specifications with additional types of technology shocks will follow.

For this exercise,I augment equation 19 into a three-factor production function where the labor input is now decomposed into skilled (N_t^s) and unskilled (N_t^u). The assumption that firms only utilize a single capital augmenting technology is maintained. Additionally, rather than assuming a Cobb-Douglas functional form, I follow Lindquist (2005) and Krusell et al. (2000) and use a CES production function with varying elasticities of substitution between the production input factors. This design is meant to allow for capital-skill complementarity, as introduced above. The new function then becomes

$$Y_t = \left[\mu(N_t^u)^\sigma + (1-\mu)(\lambda(K_t A_t^k)^\rho + (1-\lambda)(N_t^s)^\rho)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}}. \tag{22}$$

The parameters μ and λ govern income shares. The parameter, σ, governs the elasticity of substitution between unskilled labor and capital and skilled labor, whereas ρ governs the elasticity of substitution between capital and skilled labor. In theory, capital-skill complementarity holds if $\rho¿\sigma$. The approach in this paper is to empirically determine if changes in A_t^k also drive the efficiency in N_t^s.

For empirical estimation, I redefine the variables in the original bivariate SVAR such that $\Delta x_t = [\Delta Q_t, \Delta N_t]$, where ΔQ_t is the first log-difference of the relative price of consumption goods to investment goods, and ΔN_t denotes the first log-difference of the skill-ratio (i.e. the proportion of skilled labor hours to unskilled labor hours). To identify the IST shock, I assume that the skill-ratio has no permanent effect on the relative price, only an IST shock does. The impulse responses are presented in figure 9. Firstly, the relative price increases after an IST shock, as per theoretical expectations, and secondly, both variables increase after a positive shock to the skill-ratio, with the relative price returning to the initial equilibrium as per the restriction, whilst the skill-ratio rises permanently. The increase in the relative price could indicate an interesting mechanism between skill and capital innovations. It could be that skilled labor, via research and development, engineering designs, marketing strategies etc., leads to more improved innovations in capital hence the price of vintage capital declines. Such a shock would be interpreted as a positive skill supply shock. However, a positive shock to the skill-ratio could also occur when unskilled labor declines.

Meanwhile, after a positive IST shock, the skill-ratio declines on impact and immediately recovers in a hump-shape. Similarly, this decline could be a result of an increase in unskilled labor or a decrease in skilled labor[17]. In a single-technology model, these results do not have significant innovative implications because the dynamics captured here could possibly be attributed to missing variables. As a result in the following sections additional technology shocks are accounted for, thus facilitating a comparison with pre-existing literature findings.

2.4 Multiple-technology Empirical Specification

In this section, I analyze the dynamic effect of an IST shock on the skill ratio, in a specification where two types of technology shocks are identified. The second type is the neutral

[17] I specifically address this issue in a later section.

technology shock, and it is denoted A_t^* in the production function below

$$Y_t = A_t^* \left[\mu (N_t^u)^\sigma + (1-\mu)(\lambda (K_t A_t^k)^\rho + (1-\lambda)(N_t^s)^\rho)^{\frac{\sigma}{\rho}} \right]^{\frac{1-\alpha}{\sigma}} . \tag{23}$$

This technology is neutral in the sense that it improves efficiency in the production of both capital and consumption goods, for both skilled and unskilled labor. Fundamentally, the empirical estimation here could be viewed as a combined extension of the work by Fisher (2006) and Ho (2008). Ho (2008) conducts a fixed effects approach where the ratio of non-production workers to total workers is regressed on TFP, relative price of investment, capital, time and industry dummy variables. He concludes that changes in IST increase the demand for skilled labor while TFP has no effect. In the preceding single-technology specification, the skill-ratio initially declines before rising to above equilibrium levels. This offers substance to the argument for a need to explore dynamism in the IST shock effect, which Ho's approach misses. Additionally, his use of workers, rather than hours, could potentially underestimate the change in the amount of effective labor input especially if workers take on over-time hours in certain years. In my application, I use hours-worked, and the SVAR methodology will extend his work to capture the dynamism of the IST effect. Also, the data I use is extended and contains relatively more recent observations. Meanwhile, Fisher provides assumptions for the identification of IST shocks in an aggregate model with more than one technology shock. With that in mind, I perform a tri-variate SVAR for the US Manufacturing sector consisting of the change in the price of consumption relative to investment, ΔQ_t, the change in the skill ratio, ΔN_t, and the growth of labor productivity, ΔY_t, in that respective order.

For identification, I adopt Fisher's two assumptions, i)that an IST shock is an additional source of permanent disturbance to labor productivity, and ii) that ΔQ_t is only affected by an IST shock in the long run. Fisher makes an additional assumption that places a numerical restriction on the effect of an IST shock on productivity, in this paper I omit it.

I restrict labor productivity disturbances from affecting the skill-ratio, and allow the skill-ratio to affect labor productivity, both being long-run restrictions[18]. The latter assumption does not contradict the restriction in the bivariate model. The assumption here is that while total labor input does not affect productivity in the long-run, the quality composition of labor input should influence productivity. The structural moving average of the model, in matrix form, is as follows,

$$\begin{bmatrix} \Delta Q_t \\ \Delta N_t \\ \Delta Y_t \end{bmatrix} = \begin{bmatrix} D(L)_{11} & D(L)_{12} & D(L)_{13} \\ D(L)_{21} & D(L)_{22} & D(L)_{23} \\ D(L)_{31} & D(L)_{32} & D(L)_{33} \end{bmatrix} \begin{bmatrix} \epsilon_t^q \\ \epsilon_t^n \\ \epsilon_t^y \end{bmatrix}, \tag{24}$$

where the matrix D is the matrix of structural impulse responses over a selected horizon, ϵ_t^q denotes an IST shock, ϵ_t^n denotes a non-technology shock, and ϵ_t^y denotes a neutral technology shock (NTS). It should be noted that ϵ_t^n is a different non-technology shock from the one identified in the previous section's bivariate model. While both could include supply-side disturbances in the labor market, the present one only refers to disturbances that alter the proportions of skilled and unskilled labor, not the total. Also, while it is assumed that changes in total labor input do not affect labor productivity in the long run, changes in the quality of labor input should alter long run productivity. With the ordering in 24, the model restrictions are easily attainable by imposing a lower triangular structure on $D(1)$, the long-horizon structural response matrix. As done in the previous section, this structure is achieved via a Cholesky decomposition of the $MSE(\infty)$ resulting in $D(1)_{12} = D(1)_{13} = D(1)_{23} = 0$.

2.4.1 Results

Figure 10 displays impulse response functions for the multiple-technology system presented in equation 24. The graphs on the first row are responses to a IST shock (i.e. a one standard-

[18]For simplicity, I make an assumption that neutral technology shocks are both sector-neutral and skill-neutral. Also, in a working paper, Balleer and Van Rens (2012) restrict productivity from affecting relative hours in a national aggregate application.

deviation shock to the price of consumption relative to investment). The graphs on the second row are responses to a non-technology shock (a shock to the skill-ratio), and the last row shows responses to a neutral technology shock (NTS). From the results, three points are noteworthy. Firstly, the relative price increases both on impact and permanently providing theoretical consistency of the identified shock. Secondly, the middle column shows that the skill composition of labor responds differently, on impact, to the two types of technology shocks in the system, hence the identified IST shock differs from a NTS. After a positive IST shock, the skill- ratio drops on impact and then recovers, in a humped shape, to permanent levels above the initial equilibrium. Meanwhile, a neutral technology shock yields a hump-shaped increase in the skill-ratio, although, by definition, one would expect it to have no effect. Thirdly, the effect of an IST shock on the skill-ratio changes over time, hence it can be agree that this study was a necessary extension to Ho (2008). The IST shock effects on the skill-ratio and labor productivity will partially determine the characteristic of the IST shock during the period of $1958 - 2009$. A skill-biased IST shock could offer support for capital-skill complementarity, which would perfectly explain the data dynamics observed in figure 8, i.e. that innovations of sophisticated capital induced the hiring (firing) of skilled (unskilled) labor. Meanwhile, if the IST shock is shown to be de-skilling, then additional avenues ought to be pursued to find a shock that explains the data. According to figure 10, a positive IST shock initially reduces the skill ratio (on impact) while labor productivity initially increases. Focusing on the impact responses, it can be said that the identified IST shock altered the skill composition of labor in a way that increased productivity. This could indicate a de-skilling effect of the shock. However, two points are noteworthy here; firstly, the results from the current specification only have supply-side implications i.e. they only show an initial increase in the supply of unskilled labor without any demand side implications for a complete account; secondly, a decline in the skill-ratio could come from changes in skilled or unskilled labor, hence concluding that the shock is de-skilling is premature. The first point is addressed in a later subsection. Regarding the second point, showing the response of unskilled labor would provide direct evidence on the presence or absence of de-skilling, at least on the supply side.In the following subsection, I pursue this matter by including unskilled labor in my specification.

2.5 Testing for Capital-Skill Complementarity: Supply Side Test

2.5.1 Specification with Unskilled Labor

In the preceding subsection, I established that, on impact, an IST shock alters the skill-ratio while increasing the overall productivity of labor. Specifically, it initially decreases the skill-ratio, which could be from a decline in skilled labor or an increase in unskilled labor. The former case presents a challenge because, while theoretically feasible, it seems generally far-fetched in reality, particularly in an advanced and competitive economy as the US. I argued earlier that skill can be obtained via educational advancements and internal promotion. In the US, enrollment in formal educational institutions has been increasing since the Great War, and this, supplemented by the significant turnover costs in firing experienced workers, makes a decrease in skilled labor unlikely in reality. Meanwhile, there is a greater feasibility in seeing an increase in unskilled labor after an IST shock. Technological advancements have generally simplified numerous tasks for both consumers and workers, and its adoption costs have declined over time. Consequently, in this section I investigate whether the estimated decline in the skill-ratio truly warrants a conclusion that the identified IST shock improved the productivity of unskilled labor. This would be reflected in a contemporaneous increase in unskilled labor hours. Such findings would be in contrast to the idea behind capital-skill complementarity, which views capital and unskilled labor as perfect substitutes. As a direct supply side test, I include unskilled labor to the model defined in the preceding section and study its response to an IST shock. For identifying the shocks, I propose a triangular structure to impose long run restrictions. This entails extending the assumptions already made and further restricting unskilled labor from affecting any of the variables in the long run. Firstly, I restrict unskilled labor from affecting the relative price as an extension of Fisher's assumption that only an IST shock affects the relative price. Secondly, I argue that wage adjustments will ensure that in the long run the skill-ratio recovers from any imbalance caused by an increase in unskilled labor. Specifically, an increase in unskilled labor will yield lower wages for the unskilled, hence for a better pay, workers will have to acquire skills (thus skilled labor will increase to offset the imbalance). Lastly, I argue that long run productivity should not be affected by an increase in unskilled labor. The short run increase in productivity will eventually be offset by the reduced or stagnant level of innovations expected in a market infiltrated with unskilled workers.

The results from this exercise are presented in figure 11. The skill-ratio still declines immediately after an IST shock, but in the long run it returns to the initial equilibrium. Also, in this model labor productivity appears to be unaffected by an IST shock on impact, although the response is not statistically significant and it decreases eventually. Since the responses of the relative price and the skill-ratio are consistent with previous specifications, the identified shock is the same IST shock as identified before. Meanwhile, unskilled labor increases contemporaneously after an IST shock, before dropping to levels below the initial equilibrium. After a NTS, unskilled labor drops and recovers in a humped shape, as is normally the case with labor input and neutral technology. The results from this specification are consistent with the notion of a de-skilling IST shock, and offer no support for capital-skill complementarity in US Manufacturing. The two key qualifying conditions are that this is only on impact, and only demonstrated the supply side of the labor market.

2.5.2 Demand Side Test: Specification with the Skill Premium

The results obtained so far depict an initial de-skilling effect of the IST shock. However, as pointed out above, they are mainly from the supply side of the labor market, i.e. they have only shown that after an IST shock the supply of unskilled labor increases. For an all-round demonstration of a de-skilling effect, I would have to provide evidence that the demand for unskilled labor also increases after the shock. This can be done via the study of the wage patterns after the shock. As a result, I incorporate the skill premium into my specification. This is defined as the wage ratio for skilled and unskilled workers, and its business cycle behavior patterns have been linked to skill-biased technology shocks. This can be seen, for the aggregate production function, in papers such as Katz and Murphy (1992), Autor, Kratz and Krueger (1999), Krusell et al. (2000), Acemoglu (2002). For sectoral production functions, notable papers to have modeled skill premium include Kahn and Lim (1998), and Berman et al. (1994). The effect of an IST shock on the skill-premium also serves as a more direct test for capital-skill complementarity as well. Recently, Lindquist (2005) designed a dynamic general equilibrium model that allows for capital-skill complementarity, and found that it explains business cycle fluctuations in the skill premium better than a model without capital-skill complementarity. He thus concluded that this complementarity is an important factor for wage inequalities over the business cycle.

In this paper, the wage patterns displayed in figure 8 also call for a consideration for wages in my empirical specifications. In testing for capital-skill complementarity, I observe the dual effect of a positive IST shock on both the skill-ratio and the skill premium. An increase in the skill premium after an IST shock signifies both skill-bias and capital-skill complementarity. An increase in both variables after the shock would be indicative of a presence of capital-skill complementarity, whereas a decrease in the skill premium offers no support for capital-skill complementarity. Additionally, Lindquist(2004) argues that capital-skill complementarity tends to produce a pro-cyclical (increasing) skill premium, thus emphasizes that a skill premium decline offers no evidence of capital-skill complementarity. The relationship between the skill premium and the input factors can be seen by taking first order conditions for equation 23, which yields the following expression for the wage ratio[19]

$$\frac{W_t^s}{W_t^u} = \frac{1-\mu}{\mu}(1-\lambda)\frac{\sigma}{\rho}\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right]^{\frac{\sigma-\rho}{\rho}} \left(\frac{N_t^u}{N_t^s}\right)^{(1-\sigma)}, \tag{25}$$

and taking the logs yields

$$log\left(\frac{W_t^s}{W_t^u}\right) = \frac{\sigma}{\rho}\frac{1-\mu}{\mu}(1-\lambda)\frac{\sigma-\rho}{\rho}log\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right] + (1-\sigma)log\left(\frac{N_t^u}{N_t^s}\right). \tag{26}$$

[19]The full derivation is presented in Appendix A.

Based on the expression above, my specification includes the relative price, the skill-ratio and the skill premium. Under capital-skill complementarity, A_t^k would increase the skill premium since in that case $\sigma > \rho$ would hold. Given the nature of the raw data in this paper, I compute the skill premium as the ratio of wages per worker for skilled and unskilled workers. This controls for any increase in wages resulting from an increased number of workers.

Figure 12 presents the responses of the relative price, skill-ratio and the skill premium to an IST shock. As in preceding subsections, emphasis will be placed on the impact responses of each variable. It can be seen in the figure that the skill premium drops in response to an IST shock, as does the skill ratio. This offers evidence against capital-skill complementarity in US Manufacturing. Importantly, since the skill premium represents a schedule for the demand for skill, its decrease signifies a decline in the demand for skilled labor relative to that of unskilled labor. Thus it can be stated that the drop in the skill-ratio, on impact, is not merely due to an increase in the supply of unskilled labor, but also in its demand. Whilst this offers support for a compositional shift in labor demand, it is the reverse of what is shown in figure 8. Furthermore, even with the inclusion of the skill premium, the initial de-skilling effect of an IST shock remains.

2.5.3 Discussion

The results and conclusions draw so far are all based on impact results. Often, not much emphasis is placed on impact responses, but since this study uses annual data, impact responses ought to be given attention. For instance, the contemporaneous declines in the skill-ratio observed here lasts for approximately two years, which is a substantially long horizon and one that cannot be ignored. The key question to ask is whether the results warrant a conclusion that the IST shock identified in this paper does drive the labor patterns observed in US Manufacturing data between the period $1958 - 2009$? It seems that this could be a strong conclusion. The patterns in the data exhibit a long-run trend, and we saw that at longer horizons, the identified IST shock perfectly fits the data patterns. Therefore, a balanced conclusion would be that the IST shock in this paper is able to explain the data in the long run, but in the short run it fails to match the data patterns observed.

2.6 Robustness Check: a skill-biased shock from the skill premium

The failure of the identified IST shock to explain the data in its entirety implies that there might be a distinction between a sector-biased technology shock and a skill-biased technology shock, especially in the short term. It leaves open the task to identify a perfectly skill-biased technology shock. In pursuit of this goal, I revisit the growth model in Kahn and Lim (1998), in which they separately identifies efficiency parameters for each input factor as follows

$$Y_t = A_t^* F(K_t A_t^k, N_t^u, N_t^s A_t^s). \tag{27}$$

According to the interpretation in Kahn and Lim (1998), each A variable represents an increase in effective input per physical unit, thus A^s for example, is the effective input per skilled worker. The original paper does not specify the functional form attached to the production function, here I incorporate the CES as done in previous sections. The outcome is

$$Y_t = A_t^* \left[\mu(N_t^u)^\sigma + (1-\mu)(\lambda(K_t A_t^k)^\rho + (1-\lambda)(N_t^s, A_t^s)^\rho)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}} \tag{28}$$

where A_t^* and A_t^k are still neutral and investment-specific technology shocks, respectively. Taking the first order conditions yields the following equation for the skill premium

$$\frac{W_t^s}{W_t^u} = (1-\lambda)\frac{1-\mu}{\mu}\frac{\sigma}{\rho}\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(A_t^s N_t^s)^\rho\right]^{\frac{\sigma-\rho}{\rho}} A_t^s \left(\frac{N_t^u}{N_t^s}\right)^{(1-\sigma)}. \tag{29}$$

The expression above can be viewed as a demand schedule for skill. The parameter of interest is A_t^s, which will be interpreted as a skill-biased technology shock. I will identify A_t^s in a VAR setting where I will use sign restrictions to control for other sources of an increase in the skill premium. It can be seen that an increase in the skill premium can come from capital increases, a decrease (increase) in the supply of skilled (unskilled) labor, and from an increase in A_t^s. The first source is controlled for by the inclusion of the relative price in the model, and due to the findings in this paper showing that the IST is de-skilling, this also controls for the increase related to unskilled labor. What is left to control for is the increase in the supply of skilled labor. To this end, I specify a four-variable SVAR model consisting of the relative price, the skill-ratio, the skill premium, and skilled labor. I identify A_t^s from the skill premium by imposing the restriction that a shock to the skill premium should affect the skill premium and skilled labor in the same direction. This ensures that the observed skill premium hike is not due to a reduction in the supply of skilled labor.

2.6.1 Sign Restrictions

The sign restrictions will be imposed on the matrix of long run structural responses, since they are intended to be in the long-run. The procedure is as follows; I first obtain an initial estimate for the matrix B_0 defined in section 3.2, and here I denote it R. One such credible estimate could be a Cholesky decomposition of the $(MSE(\infty))$. Note that R is only just one of many possible decompositions of the $(MSE(\infty))$ to obtain B_0 with the intended structural restrictions. Different rotations of R via selections of an orthonormal matrix,Q, will impose the same restrictions. There are two commonly used methods to obtain Q, and they have been shown to equally perform well. One is the Householder approach which relies on randomly selecting a square matrix from a standard normal distribution, and using the QR decomposition until RQ satisfies the intended restrictions. The second method is the Givens Rotation which rotates R using the rotation matrix, $\begin{bmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{bmatrix}$, until the rotations sought after in RQ are satisfied. The Givens rotation matrix satisfies the orthonormal requirement by relying on the fact that $cos^2(\theta) + sin^2(\theta) = 1$. In this application I adopt the Givens rotation method to impose opposing signs on the responses of labor productivity and unskilled labor to a NTS. As a technical rule of thumb, to rotate an n x n matrix R, the orthonormal matrix Q is obtained as the product $Q = Q_1$xQ_2x......xQ_k, where $k = \frac{n(n-1)}{2}$. Each Q_i is an nxn identity matrix rotated using by the geometric rotation matrix given above. For instance, the sign restrictions in the current application are placed on the bottom-right 3x3 sub matrix for R, therefore the final rotation matrix will be given by $Q = Q_1 \text{x} Q_2 \text{x} Q_3$ where Q_i, for $i = 1, 2, 3$ are as follows,

$$Q_1 = \begin{bmatrix} cos(\theta_1) & -sin(\theta_1) & 0 \\ sin(\theta_1) & cos(\theta_1) & 0 \\ 0 & 0 & 1 \end{bmatrix}, Q_2 = \begin{bmatrix} 1 & 0 & 0 \\ cos(\theta_2) & -sin(\theta_2) & 0 \\ sin(\theta_2) & cos(\theta_2) & 1 \end{bmatrix} \text{ and}$$

$$Q_3 = \begin{bmatrix} cos(\theta_3) & 0 & -sin(\theta_3) \\ 0 & 1 & 0 \\ sin(\theta_3) & 0 & cos(\theta_3) \end{bmatrix}.$$

The values for θ_i are unique for each Q_i, and are randomly selected from a grid $[0, \pi]$, where the number of values in the grid is selected subjectively. Any Q for which RQ fits the restriction criteria is kept, and one that does not fit is discarded. Impulse responses are then calculated using each fitting RQ, and the median impulse responses are reported.

The results from this exercise are shown on figure 13. The reported solid lines represent the median impulse response functions from the draws that were consistent with the restrictions, and dotted lines are the $16th$ and $84th$ percentiles. The results seem to only show partial evidence of A_t being a skill-biased technology shock. Firstly, the impact responses to an IST shock in this model are consistent with my earlier findings. The relative price increases, the skill-ratio and the skill premium both decline, and so does skilled labor. These emphasize the initial de-skilling effect of an IST shock. Secondly, the skill premium shock identified here increases both the skill premium and skilled labor. Importantly, not only is this seen on impact, but also over infinite horizons. On its own, this can be evidence of a completely skill-biased technology shock. The interpretation is that the identified shock increased both the supply and the cost of skilled labor, hence signifies an increase in the demand for skilled labor. However, the only concern is the negative effect that this skill premium shock has on the skill-ratio, as produced by this model. If it was a truly skill-biased shock, we would expect it to increase the skill-ratio as well. Otherwise, this shock could have originated from the denominator of the skill premium i.e. an a reduction in unskilled wages from an increase in the supply of unskilled labor. A potential correction for this would be to add skilled wages and unskilled labor to the model, and impose additional sign restrictions such that a skill premium shock should affect the skill premium, skilled labor, and skilled wages in the same direction, while it affects unskilled labor with an opposite sign. An attempt at this correction for the current version of the paper proved costly both in terms of time and computer memory. A six-variable VAR requires 15 rotation matrices, and if M is the number of points in the $[0, \pi]$ grid, then the number of possible combinations is M^{15}. For a reasonably sized grid, this proved to be an effective restraint. Thus the robustness check exercise remains inconclusive for the current version of this publication.

2.7 Conclusion

In this paper, I analyzed the effect of an investment-specific technology shock on the skill composition of labor in US Manufacturing for the period $1958 - 2009$. Studies of the effect of an IST shock on total hours have already been done in the literature, hence the contribution of this paper was the analysis of the dynamic effect on the composition of labor for the chosen sample. The motivation lay in the labor compositional shifts observed in US Manufacturing data, and the goal was to determine if investment-specific technical changes can explain the compositional demand shifts. The demand shifts observed in the data could prove useful in explaining the decline in total hours often observed after productivity improvements. The intuition is that firms have been increasing (decreasing) their demand for skilled (unskilled) labor, and since there are relatively more unskilled workers, this gets projected as a decline in total hours. Therefore, an improved understanding of the forces behind the compositional shifts are useful. An investment-specific shock was of interest in this regard due to its two possible contrasting effects on labor composition. Through a series of SVAR specifications, I found that an IST shock tends to lower the skill-ratio, seemingly by increasing the productivity of unskilled labor. I showed that this led to an increase both in the demand and supply of unskilled labor. However, since the data was of low frequency, strong emphasis was placed on the contemporaneous responses. Thus the results in the paper can be taken as providing evidence that the identified IST shock is de-skilling in the short-run, but then tends towards skill-bias in longer horizons. Simultaneously, this implies that the capital-skill complementarity concept likely takes time to come into effect. As a robustness check an attempt was made to identify a technology shock that would be skill-biased throughout the entire horizon. This was a technology shock from the skill premium identified via a sign restriction VAR, and it yielded inconclusive results. While it increased the skill premium and skill supply throughout the specified horizon, it lowered the skill-ratio the entire horizon. One challenge with the skill premium shock is the inability to give it a concrete economic interpretation, otherwise it remains a latent factor.

2.8 Appendix A: A partial equilibrium growth model

Below is a simplified theoretical framework for the aggregate manufacturing sector. At time t, industries use capital and labor as inputs to produce output, Y_t. While it is common practice in the literature to model two types of capital namely, structures and equipment, I will only focus on equipment capital in this setting, and denote it by K_t. This is done because ISTC is largely associated with the production of equipment capital rather than structures, hence omitting the latter facilitates costless simplicity. Furthermore, I will divide labor input into two broad categories, skilled and unskilled labor. Different variations of such growth models often include intermediate inputs, but since the empirical section in this paper will use value-added output, their omission here is justified. Industries produce output Y_t using the following CES production function, as in Lindquist (2005), Krusell et al. (2000) and Kahn and Lim (1998);

$$Y_t = A_t^* \left[\mu (N_t^u)^\sigma + (1-\mu)(\lambda (K_t A_t^k)^\rho + (1-\lambda)(N_t^s)^\rho)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}}, \tag{30}$$

where A_t^* denotes neutral technology, while N_t^j, for $j = s, u$, denote skilled and unskilled labor input, respectively. Investment Specific Technology is represented by A_t^k.

This functional form is to enable capital-skill complementarity. The parameters, σ and ρ above govern the elasticity of substitution between unskilled labor and capital and skilled labor, and between capital and skilled labor. The function is designed to allow capital skill complementarity, as in Krusell(1998). Each industry faces production costs in the form of capital rent, r_t, wages for unskilled labor, W_t^u, and wages for skilled labor, W_t^s. The industries are assumed to participate in competitive markets and hence face market wages. Also, under free capital mobility assumption, rent is market based. Given output prices, P_t, each industry's optimization problem can be expressed as follows:

$$\underset{K_t, N_t^s, N_t^u}{\text{Max}} \; \mathrm{P}_t A_t^* \left[\mu (N_t^u A_t^u)^\sigma + (1-\mu)\left(\lambda (K_t A_t^k)^\rho + (1-\lambda)(N_t^s A_t^s)^\rho\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}} - r_t K_t - W_t^u N_t^u - W_t^s N_t^s . (31)$$

The first order conditions for optimality imply that the input cost for each factor of production equals the marginal product, as seen below:

$$\begin{aligned} r_t &= Z_t(1-\mu)\left(\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right)^{\frac{\sigma-\rho}{\rho}} (K_t)^{\rho-1}\lambda(A_t^k)^\rho & (32)\\ W_t^s &= Z_t\frac{\sigma}{\rho}(1-\mu)\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right]^{\frac{\sigma-\rho}{\rho}} (1-\lambda)(N_t)^{\sigma-1}, & (33)\\ W_t^u &= Z_t\mu(N_t^u)^{\sigma-1} & (34)\end{aligned}$$

where we have that

$$Z_t = P_t A_t^* \frac{1-\alpha}{\sigma}\left[\mu(N_t^u)^\sigma + (1-\mu)(\lambda(K_t A_t^k)^\rho + (1-\lambda)(N_t^s)^\rho)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha-\sigma}{\sigma}} \qquad (35)$$

From the above, we can express skill premium as follows:

$$\frac{W_t^s}{W_t^u} = (1-\lambda)\frac{1-\mu}{\mu}\frac{\sigma}{\rho}\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right]^{\frac{\sigma-\rho}{\rho}}\left(\frac{N_t^u}{N_t^s}\right)^{(1-\sigma)}. \qquad (36)$$

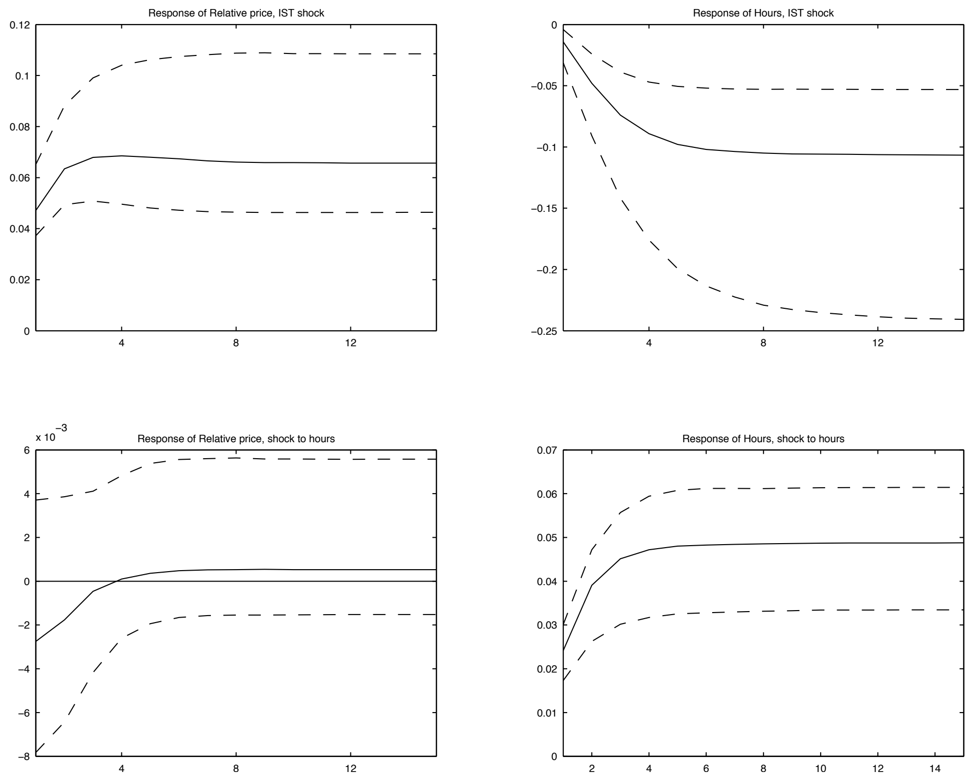
Note that $\left(\frac{N_t^s}{N_t^u}\right)^{(\sigma-1)} = \left(\frac{N_t^s}{N_t^u}\right)^{\sigma}\left(\frac{N_t^u}{N_t^s}\right) = \left(\frac{N_t^u}{N_t^s}\right)^{-\sigma}\left(\frac{N_t^u}{N_t^s}\right) = \left(\frac{N_t^u}{N_t^s}\right)^{1-\sigma}$

Taking logs yields the following expression for the skill premium,

$$log\left(\frac{W_t^s}{W_t^u}\right) = \frac{\sigma}{\rho}\frac{1-\mu}{\mu}(1-\lambda)\frac{\sigma-\rho}{\rho}log\left[\lambda(A_t^k K_t)^\rho + (1-\lambda)(N_t^s)^\rho\right] + (1-\sigma)log\left(\frac{N_t^u}{N_t^s}\right).(37)$$

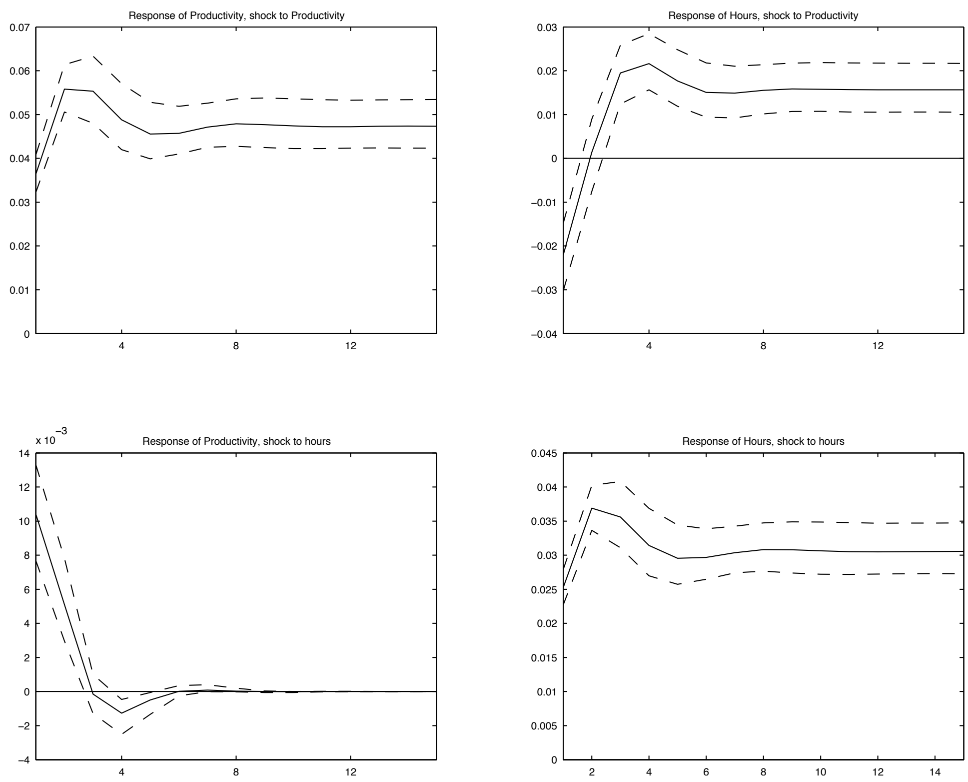
This equation can loosely be interpreted as a demand schedule for skill, and it is shown to depend on the supply of skilled and unskilled labor, capital and the accompanying technology parameter. In particular, the skill premium qualitatively decreases with an increase in the supply of skilled labor, and the opposite is true for unskilled labor.

Figure 6 – *Responses in a Single-Technology Model: an IST shock and Total Hours*



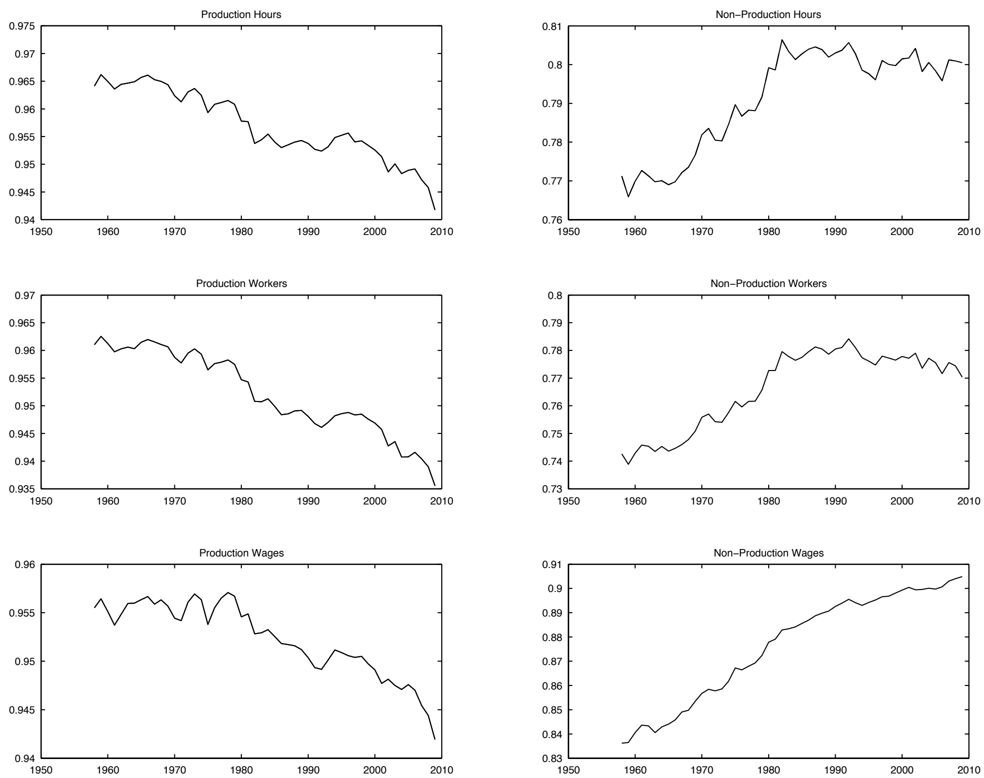
*The solid lines are point estimate impulse responses, and dotted lines are 65% bootstrap confidence intervals.

Figure 7 – *Responses in a Single-Technology Model: Neutral Technology Shock and Total Hours*



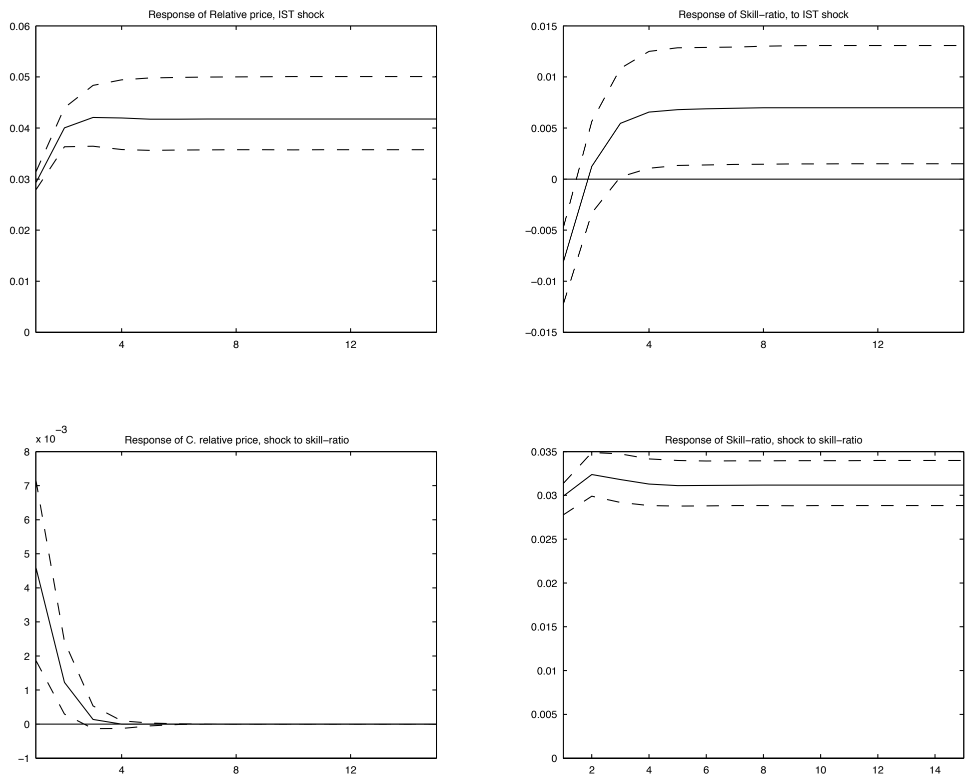
*The solid lines are point estimate impulse responses, and dotted lines are 65% bootstrap confidence intervals.

Figure 8 – *Labor Averages Across Sectors:*



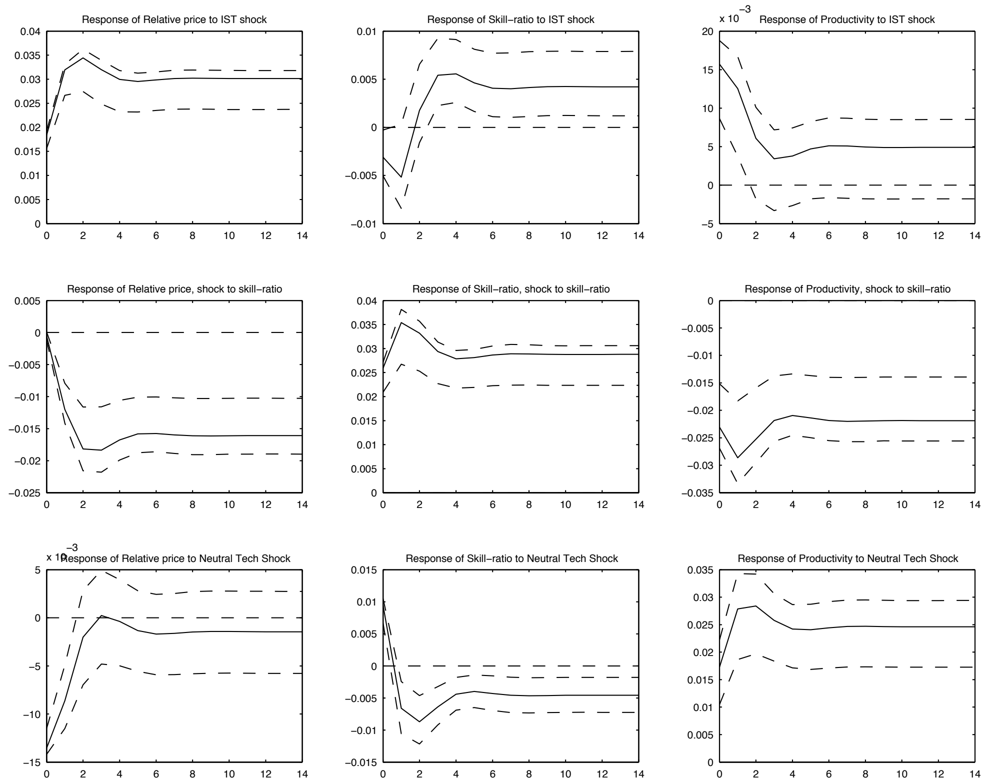
*Each variable is calculated as a fraction of the total for production and non-production workers.

Figure 9 – *Responses in a Single-Technology Model: an IST Shock and the Skill-ratio*



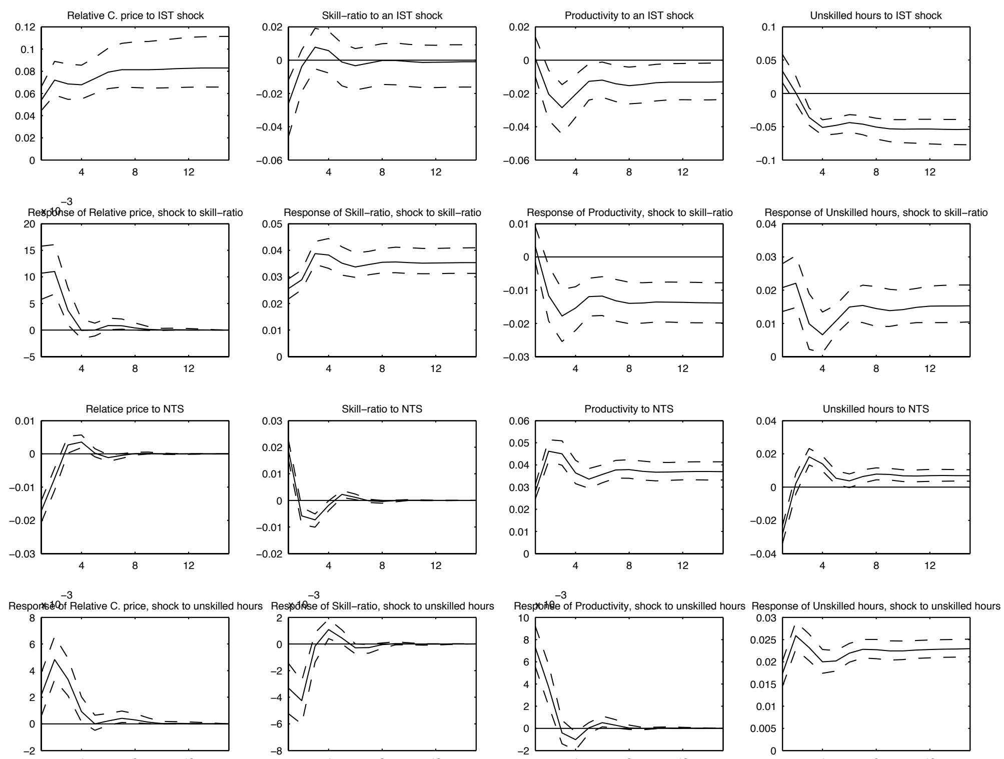
*The solid lines are point estimate impulse responses, and dotted lines are 65% bootstrap confidence intervals.

Figure 10 – *Responses in a Multiple-Technology Model*



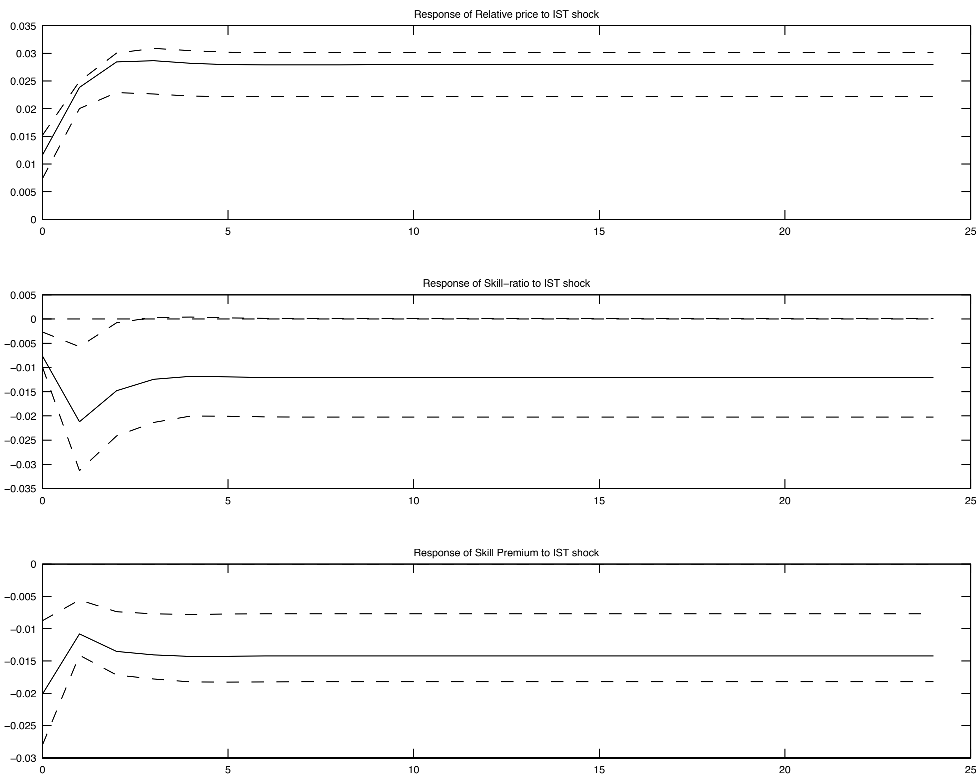
*Each column displays responses to an IST shock, shock to skill-ratio, and a neutral technology shock, respectively. The bootstrap confidence intervals are set at 65%.

Figure 11 – *Specification with Unskilled Labor:*



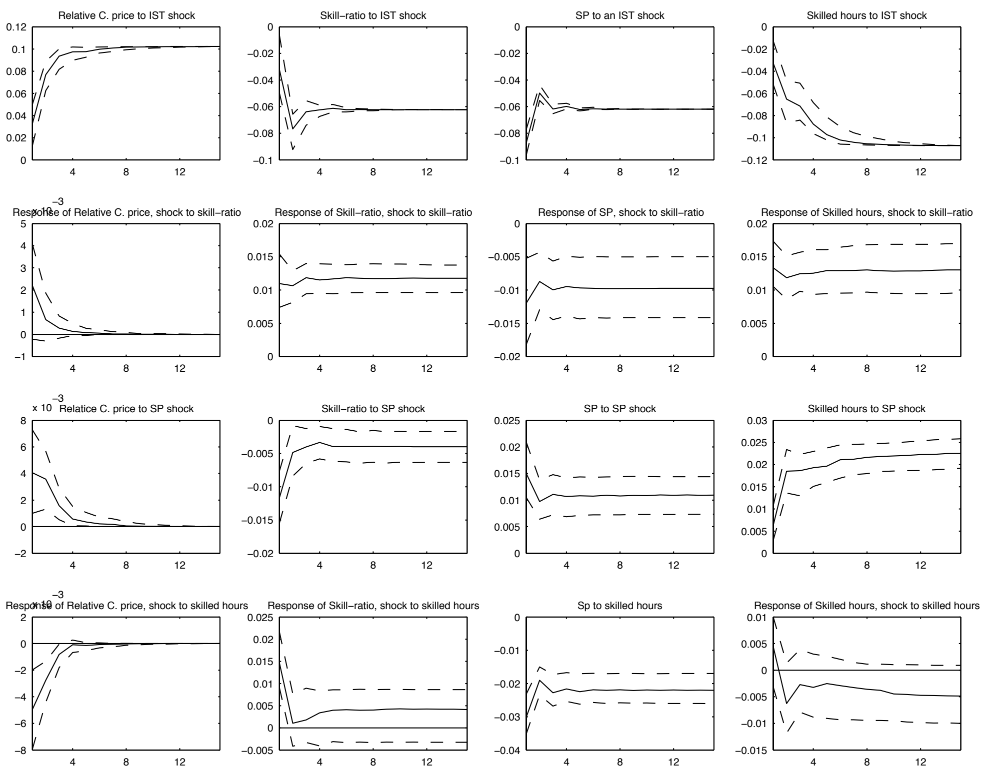
*The solid lines are point estimate impulse responses, and dotted lines are 65% bootstrap confidence intervals.

Figure 12 – *Specification with the Skill Premium:*



*The solid lines are point estimate impulse responses, and dotted lines are 65% bootstrap confidence intervals.

Figure 13 – *Specification with sign restrictions:*



*The solid line represents the median impulse response, and dotted lines are the $16th and 84$th percentiles.

3 Chapter 3
Evaluating Inflation Targeting Based on the Distribution of Inflation and its Volatility (with Dr. E. Maasoumi)

Abstract

In this paper the Financial Development Index (FDI) is used to rank 57 of the world's leading financial systems. Its calculation is based on the following 7 economic pillars: (1) Institutional environment,(2) Business environment, (3) Financial stability, (4) Banking financial services, (5) Non-banking financial services, (6) Financial markets, and (7) Financial access. Pillar (4) is constructed from bond markets, stock markets, foreign exchange markets, and derivative markets. Pillar (5) includes a country's IPO activity, namely the IPO market share, IPO proceeds amount, and IPOs share of world IPOs. The stock market index provides a short-term account of financial activities, whereas the FDI provides a long-term broader account of the financial structure and health of an economy. As the performance and success of a given monetary policy would less likely be judged on short-term dynamics, it seems sensible to use the annual FDI as one of several economic and country attributes in a policy evaluation of Inflation Targeting. The paper offers a potential outcomes analysis of the impact of inflation targeting on inflation and inflation volatility, and focuses on advanced economies that adopt "inflation targeting" as a formal monetary policy. In order to deal with the counterfactual question, namely what would be the inflation rate for an adopting country had it not adopted this policy, the paper offers a new matching technique that subsumes the traditional Propensity Scores methods as a special case. The paper has different proposals for assessing "matching" based on the whole distribution of any "scores". Additionally, the paper goes beyond the Average Treatment Effect (ATE) and examines the entire distribution of inflation and its "variability". It is found that the adoption of Inflation Targeting has helped lower inflation (not just the mean) for the targeting countries. However, it is shown that exact numerical quantification of this policy effect is as highly subjective as choosing ideal social welfare functions. The paper also finds no evidence of a larger gain for "late adopters" of inflation targeting. As for inflation variability, there is some robust evidence of small and often statistically insignificant reduction in variability due to targeting.

3.1 Introduction

The potential effect of Inflation Targeting as a policy tool has been examined in a number of studies with the "average" impact on inflation being the main focus. In this paper, we examine the impact of targeting as a potential outcome, compared with the counterfactual outcome: what would be the inflation rate for the adopting country had it not adopted inflation targeting. We follow the general technique of "matching". This requires identification of one or more countries that are non-adopters, but with substantially identical or similar characteristics. The latter are well known multiple indicators that form a conditioning variable set in the literature for treatment effects, and Propensity Scores (PS) approach popularized by Rosenbaum and Rubin (1983).

This is a classical multiple indicator problem, an indexing puzzle, that does not seem to have been fully developed as such. To put it succinctly, how does one"represent" an economy with a single index based on multiple indicators of characteristics? Propensity Scores method is shown here to be a special "statistical" solution that obtains a [0; 1] score for each country and "interprets" these scores as treatment "probabilities". We show that this interpretation is somewhat arbitrary, and the same set of multiple indicators are capable of producing very different "scores", statistically or otherwise.

One of the main indicators in this paper is the Financial Development Index (FDI). Attempts to measure financial development in an economy can be seen in works as early as in Von Furstenberg and Fratianni (1996), who proposed the use of spreads between returns on investments and savings. Currently, the World Bank and others combine various economic attributes to rank 57 of the world's leading financial systems. Its calculation is based on the following 7 economic pillars: (1) Institutional environment, (2) Business environment, (3) Financial stability, (4) Banking financial services, (5) Non-banking financial services, (6) Financial markets, and (7) Financial access. Pillar (4) is constructed from bond markets, stock markets, foreign exchange markets, and derivative markets. Pillar (5) includes a country's IPO activity, namely the IPO market share, IPO proceeds amount, and IPO share of world IPOs. It would seem that the stock market index provides a short-term account of financial activities, whereas the FDI provides a long-term broader account of the financial structure and health of an economy. As the performance and success of a given monetary policy would less likely be judged on short term dynamics, it seems sensible to use the annual FDI as one of several economic and country attributes in a policy evaluation of Inflation Targeting based on "matching" techniques.

The first formal adoptions of inflation targeting as a significant monetary policy date back to about two decades. Advocated benefits of this policy include increased transparency, credibility, and accountability by the monetary authority. Brash (2002), and Schmidt-Hebbel and Tapia (2002) discuss the experiences of the pioneers of inflation targeting, New Zealand and Chile, regarding these benefits. Additionally, this policy is widely credited as a major contributor to lower inflation experiences of the same time period. But formal empirical studies evaluating its absolute and relative performance have produced mixed results. Ben S. Bernanke and Adam S. Posen (2002) refer to this consequential conundrum as the Inflation Targeting Debate, and the issue remains unresolved. Although there has been a general consensus that countries with a formal inflation targeting policy framework (henceforth Targeters) have experienced a downward trend in their inflation levels, a similar trend has also been observed amongst individual countries without a formal inflation targeting policy (henceforth Non-Targeters).

The challenge of identifying and isolating this policy effect is thus well suited to the potential-outcome paradigm, based on matching/propensity scores, selection bias and treatment effect regressions, differences-in-differences, as well as the traditional "structural models" approaches. An example is Ball and Sheridan (2003) whose difference-in-differences approach, controlling for initial inflation levels, produced no significant impact of inflation targeting on inflation levels. This led the authors to conclude that the observed downward trend is not necessarily due to policy changes but could merely be attributed to regression to the mean.

Following this attempt, Vega and Winkelried (2005), and Lin and Ye (2007), among others, applied a treatment effects approach to control for the potential problem of selection bias that was ignored in Ball and Sheridan (2003), and estimated the “average effect” of inflation targeting. Vega and Winkelried (2005) used a matched difference-in-difference estimator for 109 countries (23 of whom were Targeters) and found that Targeters had lower inflation levels relative to Non-Targeters. However, care should be taken in interpreting their findings because the authors increased the original sample size by including countries with greatly varying characteristics, with its attendant impact on the quality of matched Targeters and Non-Targeters . When Lin and Ye (2007) limited their sample size to only 22 developed economies (7 Targeters) they found no significant “average effect” of inflation targeting.
This paper extends the prior examinations in a number of ways: We offer an extended method of “matching” which goes beyond the Propensity Scores and subsumes it. We offer multiple indicator indices that are “ideal” in a certain strong sense, as ideal aggregators. These aggregate indices are completely new and subsume the FDI and other financial indicators enumerated above. Secondly, we emphasize the distribution of inflation outcomes, both for targeters and the counterfactual, based on their matched “non-targeters”. Also, acknowledging the possibility of longer term consistency of a policy regime, this study separates the Targeters into three groups: Late Targeters (those who have had five to ten years of targeting), Early Targeters (with ten or more years of targeting), and an “overall” which includes all targeters for any lengths of time.

Finally, we reveal a range of “average treatment effects” that are supported by the extended matching technique, making it clear that numerical quantification of inflation rate effects is more challenging and subjective than identifying a direction of change. The distributional approach lifts the “veil of ignorance” associated with focusing on mean effects, and the extended matching technique is capable of identifying robust or fragile inferences.

The information theoretic basis of our extended matching methodology was first introduced in Maasoumi and Eren (2006). Information theory is relied upon since it offers very attractive measures of diversion and distance between entire distributions. Our approach is able to provide a consistent view of the distances between entire distributions of inflation rates, including a view of the mean effects that helps direct comparison with the prior literature.

We find that the adoption of Inflation Targeting has helped to lower and stabilize inflation (not just the mean) for the targeting countries. But it is shown that statistical significance and exact numerical quantification of this policy effect is fragile, and as highly subjective as picking ideal social welfare functions! We also find no evidence of a bigger gain for "early" adopters of inflation targeting.

The rest of the paper proceeds as follows: the second section discusses the treatment effect methodology and the data used in this paper. The results from the treatment effect procedure are presented in Section 3. The fourth section performs a multiple period differences-in-differences exercise to investigate any possible contribution of regression to the mean. Section 5 considers the treatment effect of targeting on inflation variability. Sections 6 gives an analysis of the entire distributions of inflation, with Section 8 looking at the "distances" between the distribution functions of inflation rates. Section 7 provides some numerical evidence supporting ideal weights and entropy divergence parameters. Section 9 concludes.

3.2 Methodology and Data

In this paper "treatment" received or the policy event is the formal and announced adoption of an inflation targeting monetary policy by the central bank of a country, and the outcome will be the level of inflation (and later its variability over time). To put this in perspective, let Y_{it}^1 be the potential outcome for country i that is considered to be a Targeter at time t, and let Y_{it}^0 be the potential outcome for the same country i without being a Targeter at time t. Let $W = 1$ indicate that inflation targeting was formally adopted, and $W = 0$ indicate the opposite case. Lastly, let $\mathbf{X}$ be a set of multiple observable characteristics for each country. In this study the set is selected based on both theory and previous studies and it consists of the following variables: the first lag of inflation (past inflation), the growth of money supply, trade openness, an indicator of financial development, deviation of real GDP from its trend, government spending as a percentage of real GDP, a dummy variable for membership in the EU, and another dummy variable for prior use of a fixed exchange rate as a monetary policy regime.

Our initial goal is to estimate the conditional average treatment effect of the formal adoption of inflation targeting on the Targeters (ATT). This entails comparing the average outcome of the Targeters under inflation targeting $(Y_{it}^1|W = 1)$ and the potential outcome of the Targeters had they not adopted inflation targeting $(Y_{it}^0|W = 1)$. The counterfactual is a missing observation, that is $(Y_{it}^0|W = 1)$ is unobservable. Under certain assumptions (see below), the treatment effect estimated is given by;

$$ATT = (Y_{it}^1|W = 1, X) - (Y_{it}^0|W = 1, X) \tag{38}$$

$$= (Y_{it}^1|W = 1, X) - (Y_{it}^0|W = 0, X) \tag{39}$$

The reliability of the obtained estimates depends on a high level of similarity in the characteristics of the matched Targeters and Non- Targeters. To see clearly how this works one ought to first conceive the adoption of inflation targeting in a randomized experiment and examine certain key assumptions well known in the literature such as the following:

i) If X is a sufficiently rich set of observable characteristics that predict a country's adoption of inflation targeting then the probability of adoption is independent of the potential outcomes i.e.

$$
\begin{aligned}
W &= 1 \\
&= 1 \perp Y_{it}^{1}, Y_{it}^{0} | X_i .
\end{aligned}
$$

This is known by various names including conditional independence, selection on observables, or unconfoundedness.

ii) For every value of the observed characteristics each country has a positive probability of adopting inflation targeting, i.e. $0 < prob(W = 1|X_i) < 1$. This is known as the overlap assumption.

iii) An additional condition for increased matching accuracy is a significant overlap between the characteristics of the matched Targeters and Non-Targeters. Such an overlap is referred to as common support and it ensures that the matched entities exhibit substantial similarities. It is often achieved via eliminating the entities (countries) with treatment probabilities/scores very close to either one or zero.

Propensity scores may be used in a number of ways. Rosenbaum and Rubin (1983) showed that conditioning on the propensity scores rather than the raw observables satisfies the second assumption above as well i.e. $0 < prob(W = 1|e(X_i))$¡ 1 where e(X_i) is the propensity score. But entities may be matched directly based on several different measures of “closeness” between their propensity scores.

3.2.1 Matching

As stated above, maximizing the similarity between the treated and the counterfactuals is a crucial step. This paper pays additional attention to the concept of “matching”. Propensity Score matching has been the standard method, as in Vega and Winkelried (2005) and Lin and Ye (2007). The principal challenge here is a multidimensional comparison of two entities based on dimensions of observed X. This is a large subject matter outside of the treatment effect literature which appears to have been ignored within the PS literature. For a latest example for developments and challenges in multidimensional characterizations see Decancq and Lugo (2013). These challenges concern the questions of what weights are appropriate for each dimension, what degree of relationship (substitution or complementarity) exists between different dimensions, the interplay between the latter two questions, and heterogeneity among population members, among others. We will see shortly that PS is a relatively narrow "aggregation" technique that addresses these questions, implicitly, and non-optimally. We propose a decision theoretic mechanism for selecting the "aggregator" functions that include PS, especially the linear index model favored in much of the PS literature. Essentially this is an aggregation or "Score" function which takes the form of a generalized hyperbolic mean:

$$S_i \quad = \quad (\sum_{j}^{m} \alpha_j X_{ij}^{-\beta})^{\frac{-1}{\beta}}, \beta \neq 0, \tag{40}$$

where the weights placed on each covariate must sum to one, for example $\alpha_j{=}\frac{1}{n_x}$, with n_x being the number of elements in X. β is the substitution parameter, and is also related to entropy measures. We note that generalized geometric mean ("Cobb-Douglas") is a special case when $\beta = 0$.

This aggregator function was developed by Maasoumi (1986) as an ideal composite of several dimensions that characterize an entity, be it an individual, a country, or a household. Its derivation comes from minimizing, with respect to S, the following Multivariate Generalized Entropy measure of closeness and affinity between the whole distribution of the aggregator S, and the distributions of all of its constituents, the several dimensions in X:

$$D_\beta(S, X; \alpha) \quad = \quad \sum_{j=1}^{m} \alpha_j \{ \sum_{i=1}^{n} \frac{S_i[(\frac{S_i}{X_{ij}})^\beta - 1]}{\beta(\beta+1)} \} \tag{41}$$

Since all of the objective information about a variable is summarized by its distribution, no other aggregation score can be more efficient than S. The S functions cannot be beaten based on objective data-based criteria. But there is no a priori strong rule for selecting parameter values such as the "weights" (α), or the substitution parameter (β). Maasoumi (1986) provides a discussion of the axioms that underly measures of divergence and entropies. But, as discussed in Granger et al. (2004), there is a special place for $\beta = -1/2$, as it is the only measure that is also a metric, and therefore especially suited for the type of "distance" assessments that are made for matching exercises where the triangularity rule must be satisfied. Below, we report results based on select values of the unknown subjective parameters. In addition, in section 7 we briefly report on a numerical search method to find the minimum of the criterion function (4) over a fine grid of values for β and α. Interestingly, we find $\beta = -1/2$ is also the "optimum" value! Estimation of these deep preference parameters must be viewed with caution. They are subjective and likely as divergent as social preference functions.

Maasoumi and Eren (2006) apply the generalized hyperbolic mean to data from Dehejia and Wahba (2002) to estimate the treatment effect of participation in the National Supported Work Demonstration on real earnings in 1978. They assessed its matching performance over a range of values for the weights and substitution parameter (based on the Kullback-Leibler measure of divergence between entire distributions), and compared it to propensity score matching. The fragility of inferences is made amply clear for the treatment effect, as is the arbitrariness of the PS method, especially when based on the probit/logit of a linear index of X. It helps to see the relationship between the S scores and the traditional PS: Note that at $\beta = -1$, the S function is linear. Suppose that at this value, we implement a probability transform with a CDF function, such as the Normal or Logistic, to obtain scores in the range $[0, 1]$. This is what probit and logit methods in effect do, in addition to conducting a maximum likelihood search for the "best" values of the α coefficients. While ML estimated coefficients are optimal in a certain statistical fit sense, it is not clear in what way they may be "optimal" as international consensus weights for the relative "value" of each component of the economy characteristics included in X! Further, the attribution to the PS so estimated as "the probability of treatment" is not within the realm of objective scientific examination. It is a paradigm assumption. In our empirical work here, we consider the probability transforms of S functions, with and without estimated α values from a regression, to allow direct comparison and to place in context the PS assessments.

3.2.2 Data and Empirical Analysis

The data used in this study is a panel of 30 countries all described as advanced economies by the IMF. The data is annual and ranges from the year 1980 to 2007. The end date was chosen to avoid the global economic instability triggered by the financial crisis. Our panel differs from that used by Ball and Sheridan (2003), and Lin and Ye (2007) in that it provides for more observations since it has slightly more countries and covers a relatively longer time period. It also differs from that of Vega and Winkelried (2005) in that it has countries that are relatively less different in terms of economic status. The period of "great recession" since 2008 is characterized by fear of deflation and high unemployment, with aggressively expansionary monetary policy. In this environment, it would be difficult to designate any of the major countries as targeting inflation, notwithstanding prior designations. Including data for post 2008 period would challenge identification of the policy effect we are aiming to isolate.

The growth of annual Consumer Price Index (CPI) is used as a measure of inflation, and broad money is used to measure money supply (these two variables were obtained from the IMF's International Financial Statistics). Real GDP per capita, government spending, and trade openness were all obtained from the Penn World Tables, whilst the Financial Development Indicator was obtained from the World Bank's World Development Indicators. Data on EU membership and fixed exchange rate regime was obtained from individual central bank websites and from the official European Union website. As for the adoption dates for Targeters, we follow Ben S. Bernanke and Adam S. Posen (2002), Ball and Sheridan (2003), and Lin and Lin and Ye (2007) who use the year of the first quarter in which an official target was announced. These dates coincide with those collected from individual central bank websites as well. Two countries adopted and later dropped inflation targeting. These are Finland and Spain who both joined the European Monetary Union.

Table 7 – *Summary Statistics:*

Country	IT	Inflation	Trade	Financial Dev't	Money Growth	Govt. Spending	GDP
Australia	1994	4.81	36.56	63.88	0.22	13.43	26429
Austria	-	2.81	79.37	92.24	0.17	12.75	27381
Belgium	-	3.11	142.93	55.96	0.28	15.67	25726
Canada	1991	3.77	63.94	108.65	0.38	14.74	27291
Cyprus	-	4.26	105.93	150.93	0.16	12.64	16501
Denmark	-	3.81	76.87	75.23	-1.02	19.05	26061
Finland	1993-97	3.86	62.99	65.70	0.21	17.54	23028
France	-	3.83	47.47	90.62	0.08	17.39	24170
Germany	-	2.23	55.90	97.49	0.57	13.05	25472
Greece	-	11.87	50.31	44.44	-0.05	14.33	19051
Hong Kong	-	4.4	266.16	149.01	0.14	4.17	27944
Iceland	1992	16.52	71.68	76.07	0.17	17.01	27924
Ireland	-	5.41	130.84	78.05	-0.05	11.58	22993
Israel	1992	50.76	73.59	70.59	-0.69	26.13	18909
Italy	-	6.14	45.21	63.76	-0.18	12.96	23732
Japan	-	1.24	22.24	183.93	-0.23	12.35	25782
Repub. of Korea	1998	5.90	68.98	70.68	-0.26	10.21	14182
Luxembourg	-	3.19	220.57	103.98	0.08	8.71	49040
Malta	-	3.00	162.50	84.00	-0.01	14.73	14968
Netherlands	-	2.59	116.50	107.66	0.81	17.67	26633
New Zealand	1990	5.76	58.61	78.57	0.60	15.57	19499
Norway	2001	4.38	72.97	71.35	0.39	15.26	34905
Portugal	-	9.29	64.25	89.40	0.0008	13.40	15738
Singapore	-	1.96	365.70	103.15	-0.97	6.46	26399
Spain	1994-98	6.09	45.39	91.38	0.01	12.55	20886
Sweden	1993	4.43	72.74	97.29	0.08	23.18	24358
Switzerland	2000	2.28	76.33	151.14	0.75	6.80	32101
Taiwan	-	2.79	99.19	68.66	0.14	12.05	15720
United Kingdom	1992	4.78	53.69	105.38	0.24	17.00	23306
United States	-	3.85	22.10	141.25	0.36	9.97	33312

3.3 Results

This section presents the traditional average treatment effect on the treated (ATT) of inflation targeting. We present results for both the traditional PS method, and based on our hyperbolic mean Score functions. We also offer a sensitivity analysis by varying parameters (β and α) used in computing the latter. Specifically, we first present ATT estimates obtained via Propensity Score matching in which the covariate set ($\mathbf{X}$) used in the probit regression is the same as that used in the computation of the hyperbolic mean. Secondly, we present the estimates obtained under hyperbolic mean matching for a selected set of betas (β=\{+/- $\frac{1}{8}$, +/- $\frac{1}{4}$, +/- $\frac{2}{3}$, +/- $\frac{3}{4}$, +/-1\}), each beta used with three kinds of alphas as follows: i) $\alpha_j = 1/n$ where n is the number of covariates in($\mathbf{X}$), ii) different alpha values such that $\sum_{j=1}^{n} \alpha_j = 1$ where α_j, the weight of each covariate in the computation of the functional form, is determined by each covariate's average marginal effect on the likelihood of adopting inflation targeting, and iii) α_j is the weighted coefficient of each covariate in a linear index probit regression. When $\beta = -1$, this last set of probit weights is directly comparable with the linear index PS matching results (slight differences due to the absence of an intercept in our score functions).

Three sets of results are presented based on the length of time targeting has been in effect: any length (denoted Overall), the formal adoption of targeting for at least five years but less than ten years (Five Years), and formal adoption of targeting for at least ten years (Ten Years). We report estimates from the commonly used One-to-One matching method, and results from alternative multiple matching methods (radius, kernel, local linear, and nearest neighbor) are qualitatively consistent and can be provided upon request. With One-to-One matching each Targeter is matched to only one Non-Targeter. This method allows the use of matched pairs when evaluating the "similarity", of their entire distributions, an exercise that we also carry out below.

3.3.1 Inflation Level

Table 8 presents the estimated ATTs of adopting an inflation targeting policy on the level of inflation. The first two columns specify the parameters (β and α) under which the hyperbolic mean is calculated (here $\beta > 0$), and the remaining columns respectively show the estimated overall effect, the effect after 5 and 10 years of targeting. As seen on the table, we obtain ATTs whose negative sign is robust to the matching tools and variations of the hyperbolic mean parameters. This is an implication that on average the level of inflation for Targeters has been lower at the mean than that of Non-Targeters over the chosen sample period. However, important ATT differences still exist between our score functions and PS. Propensity Score matching, for instance, yields estimates that are both smaller and mostly statistically insignificant (first row of the Table 8). Such estimates could prompt one to argue for a very subdued and largely insignificant contribution of inflation targeting in the chosen sample.

However, this clearly contrasts with results obtained via our various hyperbolic means, where 49 out of 54 estimates are significant at the 1% level, 4 at the 5% level, 1 at the 10% level, and only 1 is statistically insignificant, indicating a strong influence of IT in lowering inflation levels for Targeters. One interpretation is as follows: The linear index function specifies infinite substitution between components of X! They are effectively "the same" as far as characterizing the economy. When this level of substitution is made finite, with other values of β, different influences are exerted by different components of the economic variables in X, aside from the weights attached to each. This seems to raise the ATT for a wide range of the substitution and weight parameters. It also suggests that the corresponding implicit values of these same parameters may be close to the boundary sets, since they do not contradict the general inference of an average reduction in inflation by targeting.

Table 8 – *Estimated Average Treatment Effect on the Treated Across Different α and ($\beta > 0$) Values*

Beta	Alpha	ATT: Overall	5 Years	10 Years
	PS Matching	-1.96	-0.45	-3.73
		(1.185)	(1.274)	(2.048)
1/8	1/8	-2.33**	-2.95***	-2.85**
		(0.636)	(0.708)	(1.052)
	Diff Weights	-3.57***	-2.81***	-3.13***
		(0.668)	(0.638)	(0.677)
	Prob Coeff	-3.38***	-2.24***	-2.58***
		(0.636)	(0.509)	(0.949)
1/4	1/8	-3.20***	-3.88***	-3.84***
		(0.642)	(0.812)	(1.074)
	Diff Weights	-3.32***	-3.18***	-3.62***
		(0.694)	(0.733)	(0.734)
	Prob Coeff	-3.30***	-2.99***	-2.71***
		(0.694)	(0.724)	(0.724)
1/2	1/8	-3.77**	-3.76***	-3.91***
		(1.154)	(1.076)	(1.088)
	Diff Weights	-3.81***	-2.79	-2.08
		(1.097)	(1.630)	(2.249)
	Prob Coeff	-3.64***	-2.22***	-1.84*
		(0.648)	(0.501)	(0.838)
2/3	1/8	-3.72***	-4.16***	-4.36**
		(0.881)	(1.008)	(1.287)
	Diff Weights	-3.82***	-3.12***	-3.04***
		(0.602)	(0.712)	(0.735)
	Prob Coeff	-3.11***	-2.04***	-3.52***
		(0.606)	(0.653)	(0.868)

Beta	Alpha	ATT: Overall	5 Years	10 Years
3/4	1/8	-2.88***	-4.16***	-4.36***
		(0.645)	(1.008)	(1.287)
	Diff Weights	-3.77***	-2.67***	-2.71***
		(0.602)	(0.636)	(0.741)
	Prob Coeff	-2.88***	-2.91***	-2.52***
		(0.645)	(0.660)	(0.868)
1	1/8	-4.56***	-4.56***	-4.76***
		(0.781)	(0.876)	(1.174)
	Diff Weights	-3.90***	-3.07***	-2.53***
		(0.539)	(0.576)	(0.704)
	Prob Coeff	-3.79***	-4.34***	-3.83***
		(0.736)	(0.759)	(0.85)

Table 9 presents ATT estimates obtained when $\beta < 0$. We still obtain negative ATTs, mostly statistically significant and substantially larger than ATTs obtained from PS. As β approaches -1, we approach the same small negative effects obtained from the PS method, especially when the same probit estimated weights are used. Note that our S functions have the same CES forms that were proven by **?** to have a constant elasticity of substitution. The relation between β and elasticity of substitution is given by the formula $\sigma = \frac{1}{1+\beta}$. Therefore, as $\beta \to -1$ we approach perfect substitutability of these economic indicators. These indicators are not likely to be considered as perfect substitutes by most observers, hence our earlier inference that the PS results are boundary results or outliers.

Table 9 – *Estimated Average Treatment Effect on the Treated Across Different α and ($\beta < 0$) Values*

Beta	**Alpha**	**ATT: Overall**	**5 Years**	**10 Years**
	PS Matching	-1.96	-0.45	-3.73
		(1.185)	(1.274)	(2.048)
-1/8	1/8	-2.02*	-0.99	-1.25*
		(0.962)	(0.678)	(0.536)
	Diff Weights	-3.15***	-3.11***	-3.68***
		(0.691)	(0.783)	(1.030)
	Prob Coeff	-2.75***	-2.07**	-2.38**
		(0.742)	(0.702)	(0.795)
-1/4	1/8	-0.16	-1.06	-0.03
		(1.481)	(1.165)	(1.038)
	Diff Weights	-4.34**	-4.35**	-2.84
		(1.508)	(1.557)	(1.984)
	Prob Coeff	-3.41***	-2.19**	-2.01*
		(0.839)	(0.752)	(0.864)
-1/2	1/8	-1.52	-1.97**	-1.84*
		(1.00)	(0.667)	(0.829)
	Diff Weights	-1.41	-2.20	-0.36
		(1.348)	(2.057)	(1.121)
	Prob Coeff	-2.96***	-1.81**	-1.96*
		(0.808)	(0.572)	(0.777)
-2/3	1/8	0.57	-3.37	-10.46
		(0.501)	(4.10)	(0.597)
	Diff Weights	-1.91	-0.70	-0.19
		(3.402)	(1.580)	(0.158)
	Prob Coeff	-1.83*	-1.88	-1.96***
		(0.831)	(1.086)	(0.568)

Beta	Alpha	ATT: Overall	5 Years	10 Years
-3/4	1/8	-1.10	-1.05	0.72
		(1.322)	(1.60)	(2.379)
	Diff Weights	-1.06	-1.19*	-1.02
		(0.576)	(0.564)	(0.587)
	Prob Coeff	-1.80**	-1.20*	-1.54*
		(0.557)	(0.569)	(0.748)
-1	1/8	-1.78	-2.40	-2.58
		(1.195)	(1.321)	(2.243)
	Diff Weights	-0.08	-0.30	0.49
		(0.908)	(0.904)	(0.939)
	Prob Coeff	-2.10***	-2.27**	-2.92**
		(0.575)	(0.704)	(1.007)

3.3.2 Distribution of Estimated Average Treatment Effect on the Treated Under Various Parameter Specification

Figure 14 provides a graphical display of how the ATTs obtained with our hyperbolic mean change as β changes. The treatment is Overall targeting and each graph represents a different specification of α_j. The solid line is the case where $\alpha_j = \frac{1}{n}$, the green dashed line for different α_j values such that $\sum_{j=1}^{n} \alpha_j = 1$, and the red-circled line is for the case where α_j equals the probit coefficients. An average effect across the three specifications is represented by the thick dashed line. Such an average is suggestive of a significant overall contribution of inflation targeting in lowering inflation levels for Targeters. One also observes that the overall effect of IT sharply declines for β values left of -0.65, particularly for constant and probit coefficient alphas. Figure 15 displays the same information but for $\beta > 0$. Here the overall effect generally increases with an increase in beta.

Figure 14 – *Graphical Displays of the Estimated Average Treatment Effect on the Treated Across Negative Beta Values*

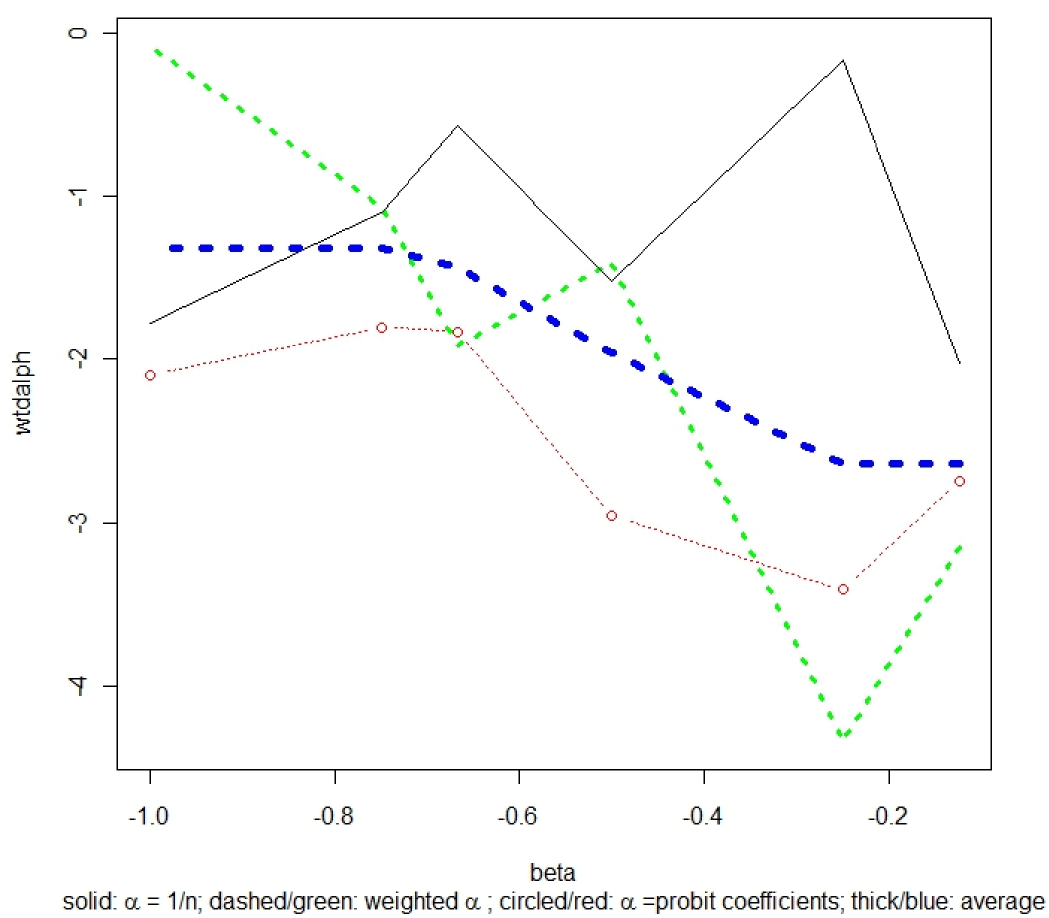
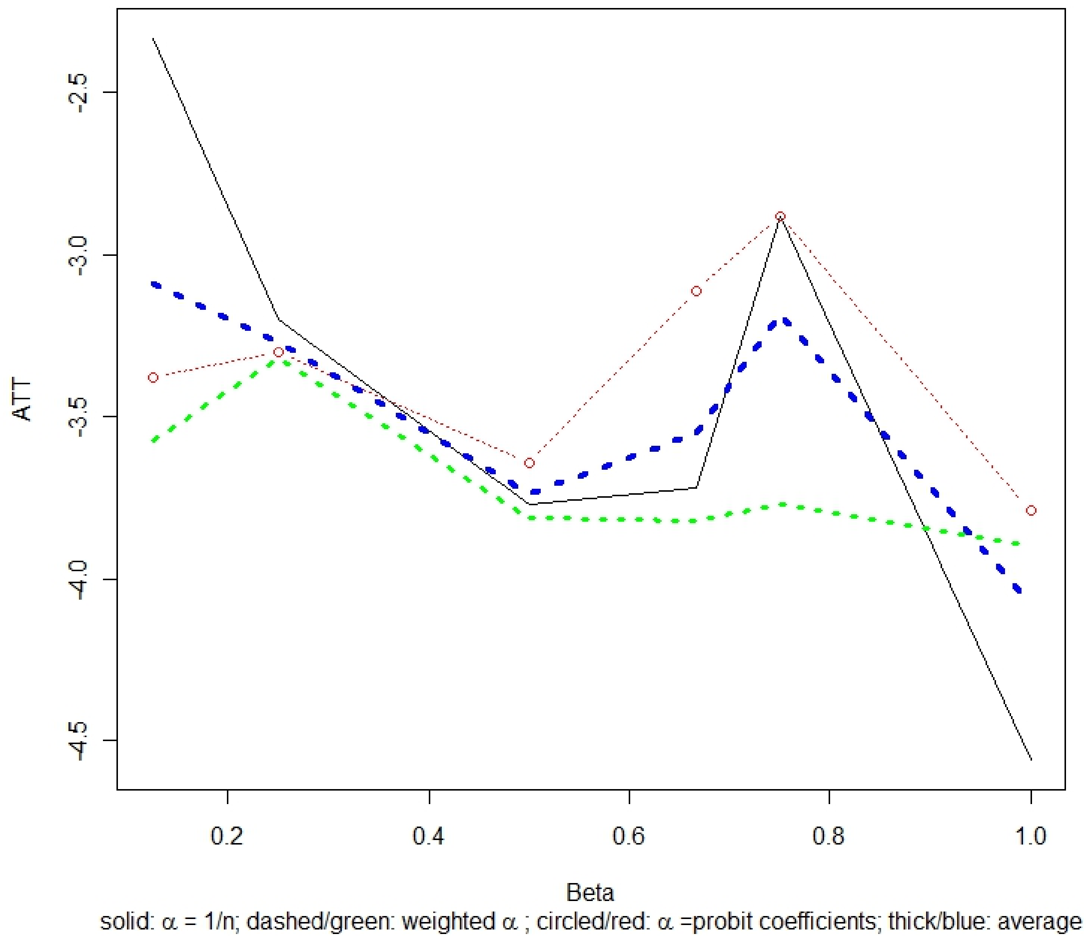


Figure 15 – *Graphical Displays of the Estimated Average Treatment Effect on the Treated Across Positive Beta Values*



In as much as our estimates are suggestive of a significant overall impact of inflation targeting on Targeters, a conclusion can not be drawn as to whether the impact grows or declines over time. The differences in the 5 year ATTs and 10 year ATTs do not warrant such a claim. Owing to the contrasting conclusions possible from the results obtained from the two matching tools, the subsection below utilizes the greater matching strengths of our tools to demonstrate the validity of the results obtained via hyperbolic mean matching.

3.3.3 A New Way of Evaluating Matching

The large differences between the ATTs obtained from the two matching tools (hyperbolic-mean and the PS) on the same data call for a closer look at their matching performance. The technique of One-to-One matching utilized herein enables the tracing and recovering of the matched Targeter/Non-Targeter pairs used in obtaining the counterfactual inflation level. We thus measure the affinity of these pairs by computing the similarity or closeness between the hyperbolic means (or propensity scores) of the matched Targeters and Non-Targeters. One appropriate tool for this exercise is the entropy measure, particularly by a metric popularized by Granger et al. (2004) that generally measures the "distance" between any two distributions. This in turn facilitates the comparison of multiple distributions in terms of either similarity, distance, or dependence. Some of the desirable properties of the entropy measure as designed by Granger et al. (2004) are as follows:

i) It is well defined for both continuous and discrete variables

ii) It is conveniently normalized to lie between 0 and 1 for continuous variates; zero if distributions X and Y are identical, and unity if there is an exact measurable nonlinear relationship between them, e.g. $Y = g(X)$

iii) It is equal to or has a simple relationship with the (linear) correlation coefficient for Gaussian variables.

iv) It is a metric i.e. a true measure of "distance" that satisfies the triangular rule.

v) The measure is invariant under continuous and strictly increasing transformations. Invariance is important since otherwise transformations would produce (e.g.) different levels of dependence between two variables.

The formula for the entropy distance measure is given by

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}(\sqrt{(}f(x)) - \sqrt{(}g(x)))^2 d(x), \tag{42}$$

where $f(x)$and $g(x)$ are marginal densities.

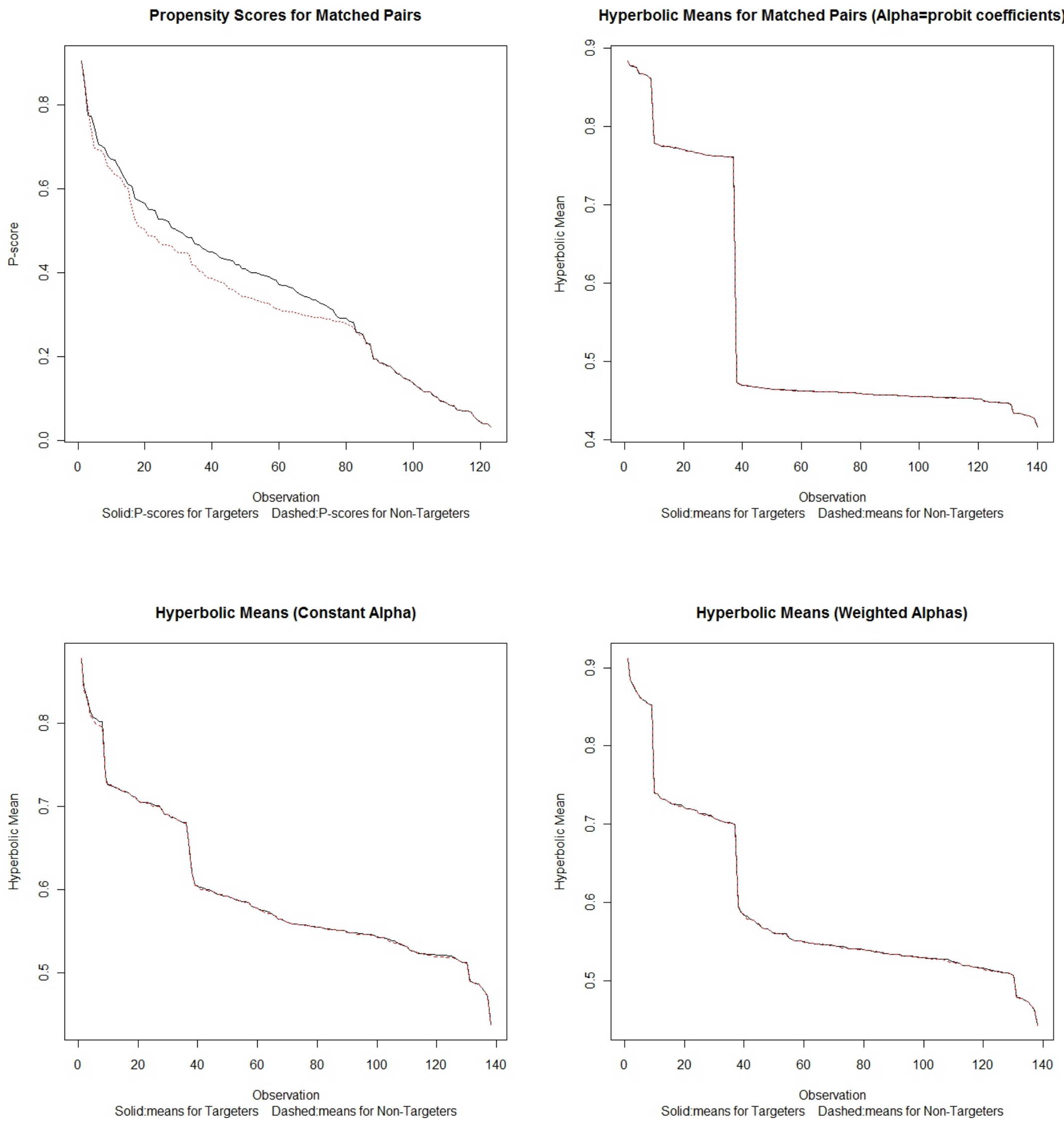
We now evaluate the distance between the distribution $f(x)$ of the Targeters' hyperbolic scores and the distribution, $g(x)$, of the hyperbolic scores of the Non-Targeters they are matched to. Entropy values are obtained for all three cases where the treatment is Overall, Five years of targeting, and Ten years of targeting. We will conduct the same exercise for the distributions of the propensity scores to evaluate PS's matching performance. A smaller entropy measure implies greater "closeness" or "similarity" between the distributions hence a better match, based on the entire distributions. For the hyperbolic score-mean we only report entropy calculations for $\beta = -0.5$ with the three variations of α_j, as seen in Table 3 below. We considered other β values but this did not alter the qualitative conclusions. The hyperbolic scores produce substantially smaller entropy distances for all the variations of the hyperbolic mean compared to the propensity scores. This is indicative of a greater closeness in the characteristics of the matched Targeters and Non-Targeters based on the hyperbolic-mean. It further confirms our earlier statement about PS matching being a boundary or outlying case.

Table 10 – *Entropies Between Distributions of Hyperbolic Means (and Propensity Scores) for the Matched Targeter/Non-Targeter Pairs*

Treatment: Overall		
Alpha	**Hyperbolicmean Matching**	**PS Matching**
1/8	1.39578e-06	0.0004568471
Weighted Alphas	0.32649-03	
Probit Coefficients	5.419207e-05	
Treatment: Five Years		
Alpha	**Hyperbolicmean Matching**	**PS Matching**
1/8	1.212895e-06	0.0003348465
Weighted Alphas	1.029983e-05	
Probit Coefficients	2.721547e-05	
Treatment: Ten Years		
Alpha	**Hyperbolicmean Matching**	**PS Matching**
1/8	3.904863e-07	0.0002508912
Weighted Alphas	2.187506e-06	
Probit Coefficients	6.819018e-06	

In support of the above results, we present, in figure 3, graphs of the actual distributions of the propensity scores (and hyperbolic means) of the matched Targeter/Non-Targeter pairs. two observations particularly stand out from the four panels in the figure; firstly, PS matching yields a relatively greater distance between the distributions of the matched pairs whereas hyperbolic mean matching yields negligible differences between the distributions. Again this signifies better similarities between matched pairs than can be obtained via PS matching. Secondly, PS matching appears to work best at matching countries with extreme probabilities of adopting inflation targeting. Since lagged inflation is one of the variables used to compute the probabilities we can expect limited differences in inflation levels for the matched pairs. This could partly account for the smaller ATTs produced in PS matching leading to an underestimated effect of inflation targeting.

Figure 16 – *Distributions of Hyperbolicmeans and Propensity Scores for Matched Pairs.*



3.4 Multiple Period Differences-in-Differences

In order to provide a well-rounded conclusion on the effect of inflation targeting we further provide a difference-in-differences estimate. In acknowledgment of Ball and Sheridan (2003)'s claim of a possible regression to the mean effect, we control for initial conditions.

Instead of the standard two-period estimation we deploy a multiple period differences-in-differences approach as given by Stock and Watson (2003). Additionally, we control for individual country and time effects leading to an estimate of annual inflation given by:

$$\pi_{it} = a + \beta_1 IT_{it} + \beta_2 \pi_{it-1} + \beta_3 C\_effect + \beta_4 T\_effect + \varepsilon_t \tag{43}$$

where IT_{it} is a dummy variable for the official adoption of inflation targeting by country i at time t, π_{it-1} is the first lag of inflation, *C_effect*, and *T_effect* are dummy variables for country and time effects, respectively. The statistical significance of β_1, our coefficient of interest, would signify an effect of the adoption of inflation targeting. On the other hand a combination of a statistically insignificant β_1, and a significant β_2 would be in support of regression to the mean. We increase the sample size for this exercise such that it now covers the period $1970 - 2007$. We also generate a subsample that excludes Israel (a Targeter), as she had six years of 3-digit hyperinflation and her country effect coefficient was statistically significant. Table 4 presents the results where the first column shows estimates obtained without controlling for initial conditions, and the second column controls for initial conditions via the inclusion of π_{it-1}. The subsample results are reported on the third and fourth columns. For the ease of presentation we do not report the 57 coefficients for C_effect and T_effect. The inclusion of π_{it-1} in the full sample reduces the treatment coefficient to almost a third of its original size (from -9.397 to -2.886) and eliminates its statistical significance. The coefficient on π_{it-1} (β_2) is positive, small and only significant at the 10% level. With such results a regression to the mean is still arguable. However, excluding Israel from the sample has important consequences. Firstly, it produces a relatively smaller but significant treatment coefficient (β_1). Secondly, upon the subsequent inclusion of π_{it-1} β_1 remains statistically significant, declining only by 61%, whereas β_2 is statistically significant at the 5% level but smaller.

Our findings prevent the drawing of a distinctive conclusion. By our model design we cannot reject a weak presence of regression to the mean, yet at the same time the adoption of inflation targeting is shown to be effective, especially after removing observations of hyperinflation.

Table 11 – *Multiple Differences-in-Differences Estimates*

	Full Sample		Without Israel	
Variable	No Lag	With Lag	No Lag	With Lag
IT	-9.397***	-2.8864	-3.5607***	-1.3780**
	(2.524)	(1.586)	(0.8177)	(0.4862)
π_{it-1}		0.7043*		0.1614***
		(0.30066)		(0.1163)

3.5 Effect of Inflation Targeting on Inflation Volatility

The impact of inflation targeting might not necessarily be limited to the achievement of low inflation levels but could also impact its volatility. This is consequential for inflation expectations. To investigate this possibility in our context we evaluate the "average" treatment effect of targeting on inflation variability (measured as the deviation of inflation from a three-year moving average). Our findings are suggestive of a negative effect of inflation targeting on inflation variability as all our coefficient estimates are negative. However, the magnitude of the coefficients are very small especially in comparison to the effect on inflation levels, and mostly statistically insignificant. As seen on Table 5 only 5 ATTs are significant at the 10% level, and 1 at the (5%) level. We even observe a few insignificant positive ATTs for the Ten year treatment. All the significant ATTs are obtained under hyperbolic mean matching with equal α_j. Lin and Ye (2007) also performed a similar investigation in the context of propensity score matching, and they found very small and largely insignificant coefficients. Their result is qualitatively replicated in our own propensity score matching exercise. In Table 4 we present results from PS Matching and Hyperbolic mean matching only for the case of $\beta > 0$.

Table 12 – *Treatment Effect Coefficients on Inflation Variability Across Different α and ($\beta > 0$) Values*

Beta	**Alpha**	**ATT: Overall**	**5 Years**	**10 Years**
	PS Matching	-0.002	-0.001	-0.006
		(0.006)	(0.005)	(0.005)
1/8	1/8	-0.0089**	-0.011*	-0.012*
		(0.004)	(0.005)	(0.007)
	Diff Weights	-0.043	-0.005	-0.006
		(0.028)	(0.011)	(0.005)
	Prob Coeff	-0.015	-0.020	-0.03
		(0.011)	(0.018)	(0.025)
1/4	1/8	-0.002	-0.0001	0.0004
		(0.004)	(0.003)	(.004)
	Diff Weights	-0.005	-0.005	0.005
		(0.006)	(0.009)	(0.005)
	Prob Coeff	-0.019*	-0.020	0.001
		(0.009)	(0.014)	(0.015)
1/2	1/8	-0.006	0.002	0.001
		(0.004)	(0.016)	(0.005)
	Diff Weights	-0.004	-0.002	0.001
		(.010)	(0.008)	(0.004)
	Prob Coeff	-0.019	-0.024	-0.026
		(0.001)	(0.016)	(0.018)
2/3	1/8	-0.005	-0.005	0.001
		(0.005)	(0.006)	(0.008)
	Diff Weights	-0.0005	-0.001	0.001
		(0.009)	(0.008)	(0.006)
	Prob Coeff	-0.009.	-0.007	0.001
		(0.009)	(0.013)	(0.009)

Beta	Alpha	ATT: Overall	5 Years	10 Years
3/4	1/8	-0.004	-0.0004	0.002
		(0.006)	(0.003)	(0.005)
	Diff Weights	-0.089	-0.005	0.0007
		(0.011)	(0.010)	(0.009)
	Prob Coeff	-0.018	-0.02	-0.03
		(0.010)	(0.014)	(0.018)
1	1/8	-0.0095*	-0.01*	-0.009
		(0.004)	(0.005)	(0.008)
	Diff Weights	-0.006	-0.006	-0.006
		(0.099)	(0.008)	(0.009)
	Prob Coeff	-0.00057	-0.0006	0.004
		(0.006)	(0.0996)	(0.0098)

3.6 Entire Distribution Analysis

It is worth noting that the evidence provided by the treatment effects estimates only concerns comparisons of inflation (or its variability) at the mean of the distribution. An interesting question that has rarely been asked relates to the effect of inflation targeting on the rest of the distribution of inflation (or its variability). This section provides a closer analysis of this effect by comparing the entire distributions of inflation for Targeters and Non-Targeters. The aim is to detect distributional differences between the country groups and also examine how the distributions for each group have evolved over time. The manner of approach here is adopted from Quah (1997) and Maasoumi et al. (2007) who produce density estimates of the distributions of economic growth rates to determine convergence (divergence) patterns amongst countries. Specifically, the procedure involves the use of robust non-parametric kernel methods to produce consistent Rosenblatt-Parzen type density estimates of the unknown PDFs and CDFs of inflation levels (and its variability). Bandwidths for the estimation are selected via likelihood cross validation. The panels in Figure 4 present the resulting PDF and CDF estimates of inflation levels for Targeters (solid graphs) and Non-Targeters (dotted graphs) in five year intervals starting from 1980 to 2005, and two additional years 2006 and 2007. The distributions shown are generally symmetric and clearly demonstrate the convergence towards lower mean values over time for both Targeters and Non-Targeters. Moreover, the shift towards lower values is not limited to the means as the same could be said of the distribution tails with high maximums of approximately 60% the 1980s, 24% in the 90s, and low maximums of approximately 7% in 2007. Of particular focus in this analysis is the post-1990 period, the era after the first formal adoption of inflation targeting. It is understood that the sole impact of inflation targeting cannot be necessarily isolated in these graphs, and that the advantage for Targeters is not very obvious, but there are some suggestive observations made as pointed out below:

i) The 1990-1995 interval is the general adoption period for the Early Targeters, and a significant improvement is seen on the Targeters' inflation distribution. In 1990 the Targeters' PDF lies largely rightward of the Non-Targeters' distribution (perhaps even an arguable case of first order stochastic dominance) implying relatively higher inflation for Targeters. However, this changes in 1995 as the Targeters' distribution shifts leftward and removes any possible stochastic dominance

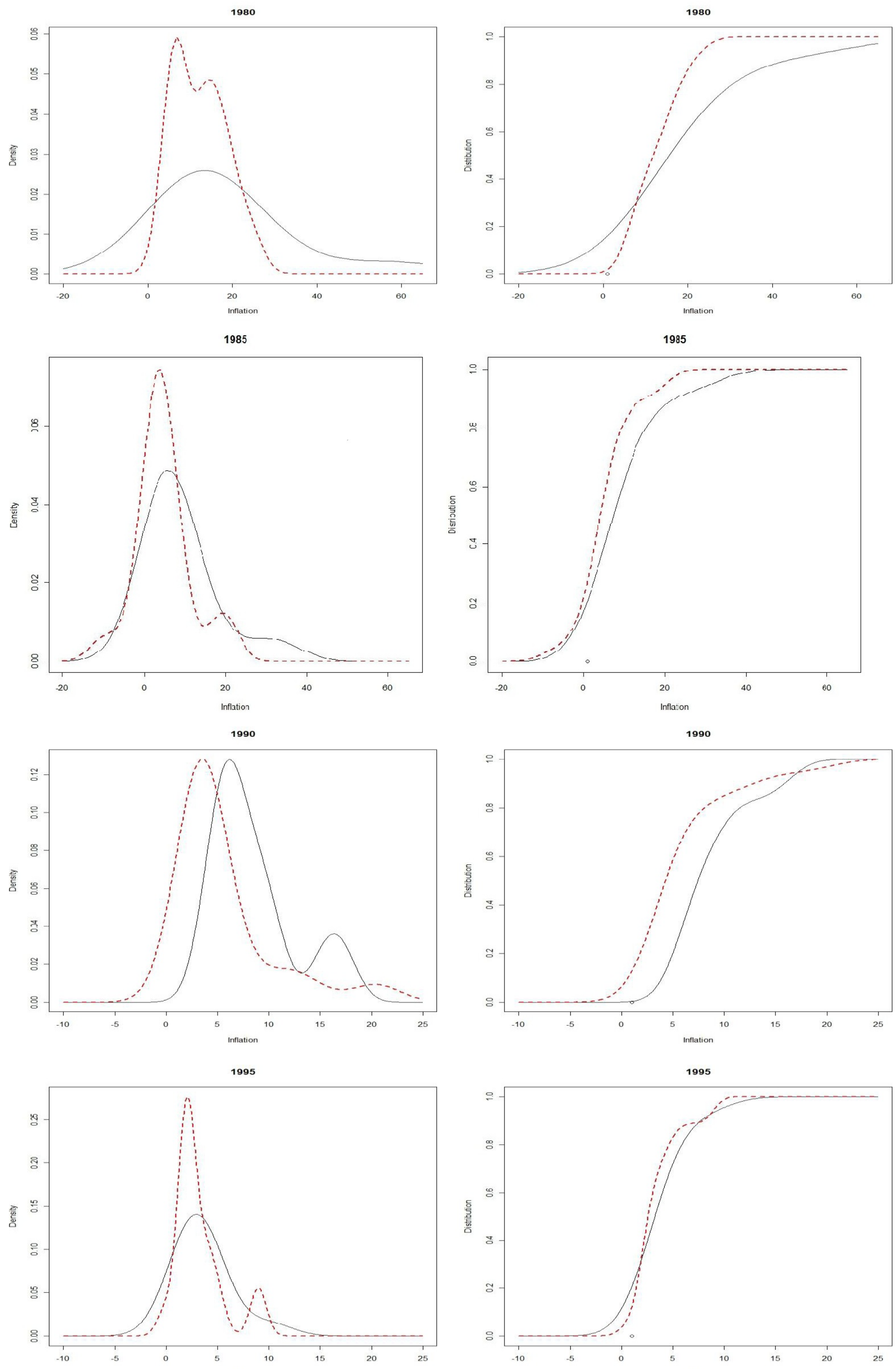
ii) Between 1990 and 1995 the left tail in the solid distribution shifts leftward of zero suggesting increased deflation among Targeters whereas the reverse seems to hold for Non-Targeters

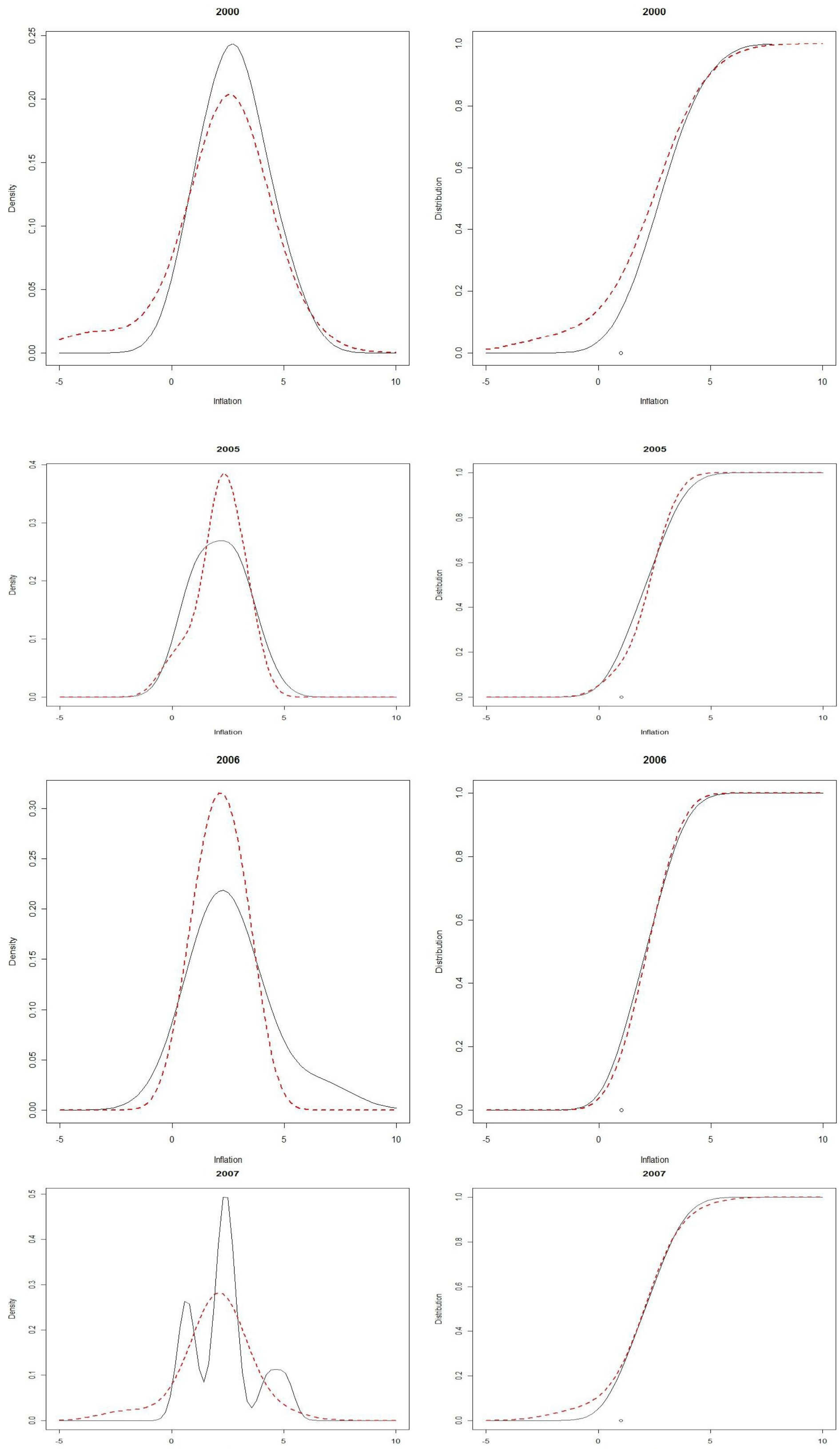
iii) Also, the period between 2000 and 2005 contains the adoption dates for Late Targeters, and we see another significant improvement for the Targeters. An evident case of first order stochastic dominance (in 2000) is eliminated in 2005

iv) Lastly, the solid PDF graphs do not differ much in the years 2000, 2005 and 2006 which could be suggestive of Targeters better stabilizing inflation than their counterparts whose graphs still fluctuate heavily

The distributional evidence supports our earlier findings in that it does not imply any significant improvement of the impact of targeting over time. However, it demonstrates an important coincidence between deflationary patterns and the adoption of inflation targeting both for Early and Late Targeters. Alternative explanations for the above noted observations can of course be arguable but such striking correlations are of great interest and taken seriously in this study.

Figure 17 – *PDFs and CDFs of Inflation for Targeters (solid) and Non-Targeters (dashed) for the Period 1980-2007*





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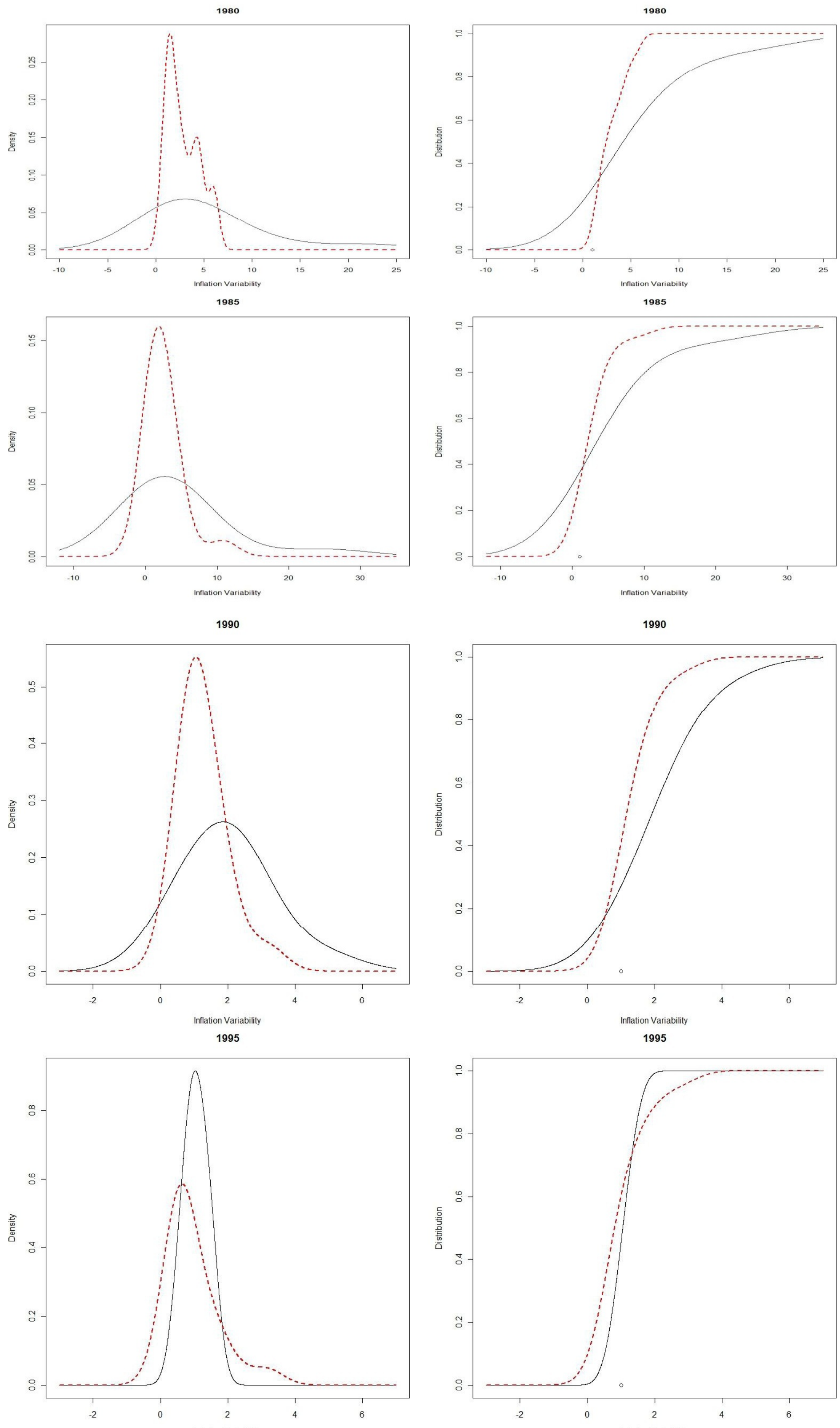
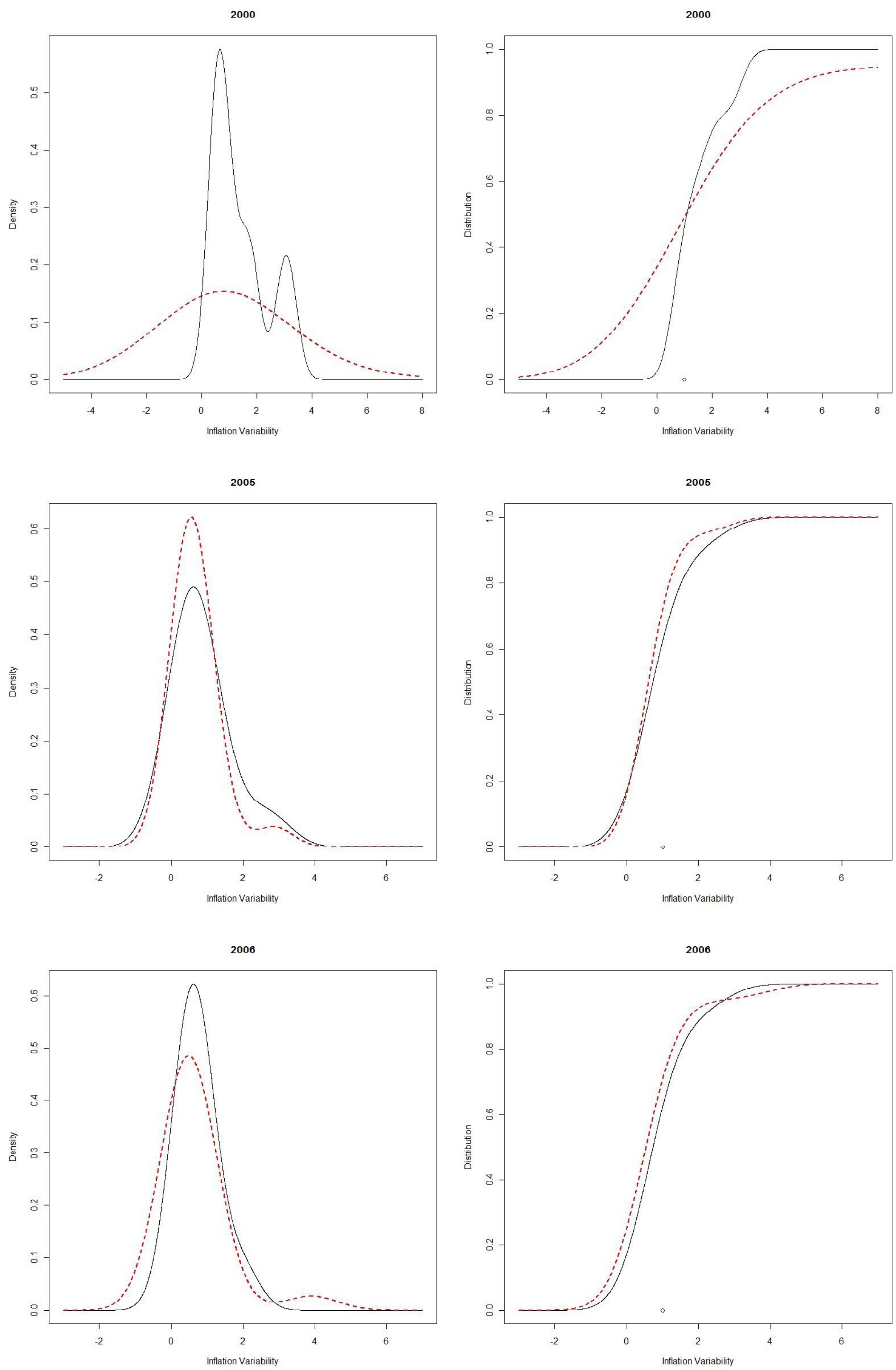
Pursuing observation (iv) above, Figure 5 provides similar estimated distributions of inflation variability for Targeters and Non-Targeters over time. Evidently variability tends to decline over time for both groups, with the Targeters starting off with relatively flatter distributions. For the same reason as stated above particular interest is placed on the post-1990 period. A well pronounced compression of the Targeters' graph is witnessed from 1990 to 1995, again coinciding with the early adoption dates for inflation targeting. Improvements between 2000 and 2005 are common between the two groups hence the IT impact is not very clear. Yet a closer look reveals that from 1995 onwards the variability for Targeters is relatively more stabilized, especially at the tails, than the variability for Non-Targeters characterized by heavily fluctuating standard deviations over time. Again this does not explicitly provide any isolated effect of inflation targeting but it does provide graphical demonstration that looking at the entire distributions of inflation variability, Targeters have not done worse than Non-Targeters and have shown great improvement after the introduction of IT.

Figure 18 – *PDFs and CDFs of Inflation Variability for Targeters (solid) and Non-Targeters (dashed) for the period 1980-2007*

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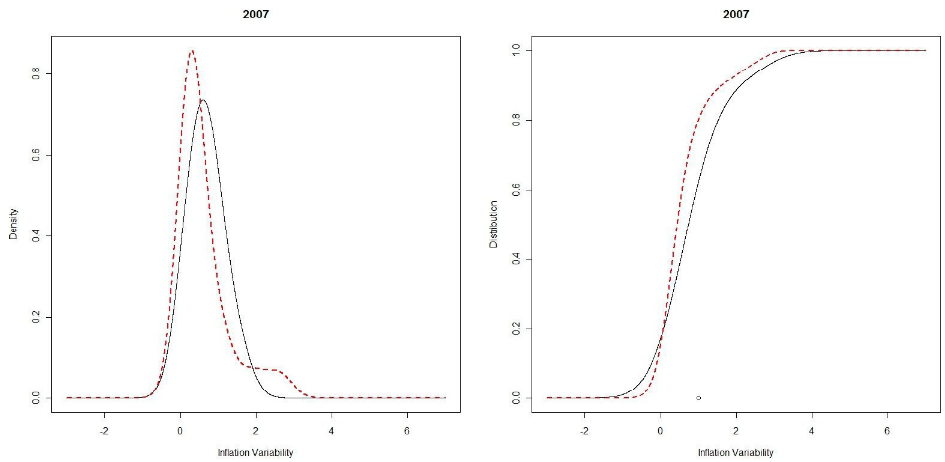

3.7 Optimum Values of Parameters

In this section we provide a brief report of a numerical search for the best values of the unknown parameters β and . The criterion to be minimized is the generalized entropy given in expression 41. For each fixed β in the range $[-0.5, -0.25, 0.5]$, we search through α values in the range $[0.1, 1]$ to minimize 41. This is done in two stages. In the first stage, we pick the "best" one hundred combinations of each beta and alphas. For each parameter combination we refine the search to obtain the "best" fifty. The latter are ranked, and the best values are reported in Table 7 with the corresponding minimum distance. The best value for β is -1/2, which corresponds to the metric entropy value! The highest α weight of .30 corresponds to the GDP component, but otherwise equal weight is optimal for other variables. The detailed results are available from the authors. We do not intend these values to be "estimates" of these deep parameters. They are intended to provide a benchmark and assist in robustification.

Table 13 – *Average Effect of Targeting on Inflation with "Best" Parameters*

Treatment	**ATT**	**Bootstrap Standard Error**
Overall IT	-2.26	1.58
5 Years IT	-2.18*	1.07
10 Years IT	-1.95**	0.61

Alpha for Inflation Lag, Money Growth, FDI, Trade, ER, EU is 0.10; $\alpha_G DP = 0.30, and \beta = -0.5;$

3.8 Entropy Distances

This section provides a supplementary analysis of the distributions presented in the section 6. Specifically, the entropy measure introduced earlier (see 42) is deployed to provide a formal quantitative report on the distances between the inflation distributions both between groups and within groups over time. The tables below present the entropy measures (denoted S_ρ) together with the 90^{th} and 95^{th} percentile values obtained under the null hypothesis of no difference in the distributions. In Table 14 we have entropies for the distributions of Targeters and Non-Targeters for each five-year interval and the additional two years $(2006, 2007)$. Firstly, apart for the years 1990, 2006, and 2007 the entropies are significantly greater than zero at the 95^{th} percentile. Hence the differences in the inflation distributions for the periods (1995 and 2005) that follow the general adoption dates for Early and Late Targeters are statistically significant. Secondly, from 1995 to 2005 the entropies demonstrate a downward trend indicating the convergence towards lower inflation levels. Constituting this trend are big drops from 1990 to 1995 and from 2000 to 2005. Table 15 shows the entropies for the Targeters' inflation distributions between five-year intervals, whilst Table 16 does the same for Non-Targeters. For the Targeters all the entropies for the interval $1995-2000$ and subsequent intervals are statistically significant at the 95^{th} percentile. Whereas only the distance between $2005-06$ are significant for Non-Targeters.

Table 14 – *Entropy Distance(S_ρ) Between Inflation Distributions for Targeters and Non-Targeters*

Year	1980	1985	1990	1995	2000	2005	2006	2007
S_ρ	**0.1540**	**0.0554**	**0.2943**	**0.2227**	**0.1070**	**0.0458**	**0.2864**	**0.4236**
90^{th} *pcntl*	0.1658	0.1857	0.1578	0.2269	0.1881	0.1011	0.1484	0.1742
95^{th} *pcntl*	0.2068	0.2224	0.1931	0.2611	0.2434	0.1363	0.1696	0.2085

Table 15 – *Entropy Measures (S_ρ) Between Inflation Distributions Across Time for Targeters*

Interval	1980-85	1985-90	1990-95	1995-00	2000-05	2005-06	2006-07
S_ρ	**0.0694**	**0.8017**	**0.2659**	**0.2694**	**0.0966**	**0.1816**	**0.3072**
90^{th} *pcntl*	0.2399	0.2986	0.1332	0.2443	0.2421	0.2034	0.1930
95^{th} *pcntl*	0.2625	0.3406	0.1556	0.2815	0.2941	0.2289	0.3115

Table 16 – *Entropy Measures (S_ρ) Between Inflation Distributions Across Time for Non-Targeters*

Interval	1980-85	1985-90	1990-95	1995-00	20000-05	2005-06	2006-07
S_ρ	**0.1603**	**0.7435**	**0.7290**	**0.2346**	**0.3470**	**0.0182**	**0.6694**
90^{th} *pcntl*	0.1226	0.2142	0.1565	0.1581	0.1146	0.0613	0.5514
95^{th} *pcntl*	0.1314	0.2500	0.2270	0.2031	0.1470	0.1174	0.1319

3.9 Conclusion

This paper offers an extension in the recently introduced branch of inflation targeting literature that uses treatment effects approach for performance evaluation. Its main contribution is an alternative matching tool that goes beyond and subsumes what has been the standard matching tool, propensity scores. Our tools, based on the hyperbolic mean of several macroeconomic and financial indicators, produces a higher degree of closeness between the matched pair of inflation targeting and non-inflation targeting countries. Our findings point to significantly lower levels of average inflation for Targeters over the period of 1980 to 2007. Similarly, average inflation variability has been lower for Targeters in the same period although this effect is dependent on accounting for the different weights attached to each observable variable in the computation of our hyperbolic function.

Furthermore, to evaluate the evolution of the impact of inflation targeting over time we we created a long separation between Targeters by five years of additional targeting. However, no significant differences are observed between the two categories warranting no claim of an improved impact over time.

Another contribution of the paper is an extension of the analysis to the entire distribution of inflation, as opposed to drawing conclusions merely based on effects on the mean. Such a study provides clear evidence of the general convergence towards lower inflation levels from all countries, not only limited to the mean but throughout the distributions. For Targeters significant leftward shifts in the distributions towards lower levels are observed around the era of formal adoption by Early and Late Targeters. Entropy measures used to measure the significance of the differences between the distributions across countries and over time provide results that attest to the above claims. Our findings support the notion that the success of inflation targeting policies is not only on average, but is extensive across quantiles and time.

Possible extensions of our work could involve applying the same techniques to Targeters in developing countries, and to evaluate how Targeters fared during the recently observed financial crisis. Also, amid future inflationary fears during the current low inflation economic recovery, should more countries adopt an inflation target as a policy trigger mechanism? Our findings provide general support for this point of view.

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