MACROECONOMIC ASPECTS OF COMMODITY PRICE DYNAMICS

by

Md Rafayet Alam

B.S.S.(Economics), University of Chittagong, 2003

Masters (International and Development Economics), The Australian National University, 2012

A Dissertation

Submitted in Partial Fulfillment of the Requirements for the

Ph.D. in Economics.

Department of Economics

in the Graduate School

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DISSERTATION APPROVAL

MACROECONOMIC ASPECTS OF COMMODITY PRICE DYNAMICS

by

Md Rafayet Alam

A Dissertation Submitted in Partial

Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy

in the field of Economics

Approved by:

Dr. Scott D. Gilbert (Co-Chair)

Dr. AKM Mahbub Morshed (Co-Chair)

Professor Sajal Lahiri

Dr. Zsolt Becsi

Professor Mark Peterson

Graduate School

Southern Illinois University Carbondale

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AN ABSTRACT OF THE DISSERTATION OF

MD RAFAYET ALAM, for the Doctor of Philosophy degree in ECONOMICS, presented on APRIL 1, 2016, at Southern Illinois University Carbondale.

TITLE: MACROECONOMIC ASPECTS OF COMMODITY PRICE DYNAMICS

MAJOR PROFESSOR: Dr. Scott Gilbert and Dr. AKM Mahbub Morshed

Fluctuation in commodity prices is a significant and timely issue to be studied. My first chapter examines the impact of monetary policy and other macroeconomic shocks on the dynamics of agricultural commodity prices. The major contributions of this study are twofold. First, unlike other studies that use indexes, this study analyzes the commodities individually, affording the inclusion of commodity-specific fundamentals such as the level of inventory -- an important determinant of commodity price -- in a structural VAR framework. Second, it exploits a rich dataset of agricultural commodity prices which includes commodities that are usually overlooked in the literature, and extracts a common factor using the dynamic factor model to understand the extent of co-movement of the prices and to gauge the extent to which macroeconomic shocks drive the 'co-movement' in a factor-augmented VAR (FAVAR) framework. The findings show that monetary policy, global economic conditions and the US dollar exchange rates play an important role in the dynamics of agricultural commodity prices.

My second chapter examines the role played by Wal-Mart in price convergence among US cities. Despite the fact that market structure is an important determinant of price convergence and that US retail architecture has been changed over the past two decades by the expansion of big box stores and supercenters, the role played by such rapidly-expanding 'big-box' chain-stores like Wal-Mart in price convergence is completely over-looked in the literature. The

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possible symmetry in costs and mark-up among Wal-Mart stores, and their influence over the city level prices motivate us to test if their presence helps price convergence among US cities. After controlling for distance, local costs such as wage and rent, and city and time specific fixed effects this study finds that prices are significantly closer in two cities if they have Wal-Mart than if none or only one of them has Wal-Mart. Though the results are mostly robust to the analysis using disaggregate price data and sub-samples, they are more pronounced for grocery items than non-grocery items, within high income cities than low income cities. Moreover, our regional analysis uncovers the regional variations in the effect of Wal-Mart on price convergence, and Wal-Mart's more prominent role in inter-region rather than intra-region price convergence. Since the presence of Wal-Mart accelerates the rate of price convergence and thus reduces the potential for misallocation of resources, our results suggest that the existence of a positive welfare impact of Wal-Mart cannot be overruled.

My third chapter uses county level data to see the effect of Wal-Mart on local economic activities and revenue in Florida. The OLS estimation shows that the presence of Wal-Mart significantly increases total retail sales and decreases sales tax rate, but have no significant effect on total taxable retail sales and total revenue from sales tax. The instrumental variable (IV) estimation shows that presence of Wal-Mart significantly decreases sales tax rate but has no significant effect on total retail sales, total taxable retail sales and total revenue from sales tax. Thus, according to our analysis, Wal-Mart does not necessarily increase local economic activities and tax revenue. However, interestingly, Wal-Mart is found to play an important role in decreasing local sales-tax rate.

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INTRODUCTION

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analysis using disaggregate price data and sub-samples, they are more pronounced for grocery items than non-grocery items, within high income cities than low income cities. Moreover, our regional analysis uncovers the regional variations in the effect of Wal-Mart on price convergence, and Wal-Mart's more prominent role in inter-region rather than intra-region price convergence. Since the presence of Wal-Mart accelerates the rate of price convergence and thus reduces the potential for misallocation of resources, our results suggest that the existence of a positive welfare impact of Wal-Mart cannot be overruled.

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CHAPTER 1

MONETARY POLICY SHOCKS AND THE DYNAMICS OF AGRICULTURAL COMMODITY PRICES: EVIDENCE FROM STRUCTURAL AND FACTOR-AUGMENTED VAR ANALYSES

1.1 INTRODUCTION

Fluctuation in the commodity prices has become a serious concern for policy makers. The sharp rise in food-price in the past decade threw millions of people in poverty (Dessus et al. 2008). At the same time, world commodity prices being notoriously volatile, economies, irrespective of importer or exporter of commodities, are affected by the external shocks that can result in economic instability and increased poverty.

The extraordinary co-movement of the commodity prices makes it impossible to ignore the influence of macroeconomic variables on the price dynamics. Growth of global income led by China and India, and monetary policy stance in the developed economies are believed to have a significant effect on the commodity prices. Lately, financialization of the commodities has also emerged as a popular explanation for the unexpected behavior of the prices. However, despite numerous studies, there is still lack of consensus on the extent to which such monetary, macroeconomic and financial shocks affect agricultural commodity prices. Particularly, the short-run dynamics of the agricultural commodity prices to such shocks warrant more investigation as different competing views are advanced by the media and academics alike. Therefore, this study aims to improve our understanding of the role played by monetary policy and other macroeconomic shocks in the dynamics of agricultural commodity prices.

This study provides several contributions to the existing literature. First, it tests for the role played by interest rates and other macroeconomic variables in the price dynamics of four

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individual commodities after controlling for their respective inventory levels. Closely related studies that examine the dynamics of the commodity prices use price-index (for example, Anzuini et al., 2013; Akram, 2009; Hammoudeh et al., 2015) and as a result cannot incorporate in their analyses the level of inventory[1]. As the level of inventory plays an important role in the determination of commodity price (Frankel, 2014; Kilian and Murphy, 2014; Krugman 2011), controlling for the inventory level in the analysis helps us to understand the role of macroeconomic shocks accurately. Studies that consider inventory in the analyses, test and report either single-equation regression results (Frankel, 2014), or long-run co-integrating relationship (Algieri, 2014). Our analysis of short-run dynamics is more relevant for (short-run) policy formulation, and the use of structural VAR methodology for the estimation is more appropriate for the evaluation of policy effectiveness (Sims 1980, 1986).

The second novelty of this study is the utilization of a rich dataset of agricultural commodity prices, which includes commodities that are usually overlooked in the literature, to extract a common factor via dynamic factor model. Testing the effect on the 'common factor' is another way to gauge the importance of macroeconomic shocks in the dynamics of commodity prices[2]. Extracting the common factor from a large number of agricultural commodities helps us understand the co-movement of the prices when commodity specific fundamentals are unlikely to be correlated[3]. Moreover, inclusion of the less-traded 'non-major' agricultural commodities

[1] Exception is Kilian (2014) who examines the dynamics of the oil price in a SVAR framework after controlling for inventory level.
[2] Since factors are different from indexes (Byrne et al., 2013), it is worthwhile testing the impact of macroeconomic variables on the common factor. In addition, factor analysis provides an idea about the extent of co-movement of the commodity prices.
[3] Analyzing the correlation among the prices of six agricultural commodities, Ai et al (2006) show that the co-movement of the prices is due to the co-movement of the commodity specific fundamentals and, thus, undercut the role played by macroeconomic variables. Since we consider

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helps us understand the extent to which they co-move with other major commodities and provides new insights into the importance of macroeconomic variables. Furthermore, unlike Vansteenkiste (2009), Poncela et al. (2014) and Byrne et al. (2013), who extract the common factor from a combined group of agricultural and non-agricultural commodities, we concentrate only on agricultural commodities. Exclusion of non-agricultural commodities such as metal, fertilizer and energy, whose characteristics and use are quite different, helps us to focus on the agricultural commodities. As agricultural commodities get different policy considerations[4], the separate analysis of agricultural commodities bears more policy relevance.

Moreover, unlike Frankel (2014) and Byrne et al. (2013), who use yearly data or Vansteenkiste (2009) and Lombardi et al. (2012), who use quarterly data, we use monthly data. Higher frequency of data is able to capture fluctuations due not only to fundamentals but also to non-fundamental causes such as speculation. Finally, this study uses a measure of Economic Policy Uncertainty (EPU), recently developed by Baker et al. (2013), to test the impact of uncertainty on commodity price. This measure is much broader, and to some extent different, than other commonly used measures of uncertainty[5]. Therefore, this study serves as a case-study of the impact of EPU on a new variable: commodity price. In sum, our study provides new insights into the role of monetary policy and other macroeconomic variables in the dynamics of agricultural commodity prices and this could help policy formulation.

fifty agricultural commodities that range from food cereals to industrial inputs, it is unlikely that commodity specific fundamentals are correlated.

[4] This is because of the nature of production and use of agricultural commodities. Unlike energy and metals which are extracted by states, agricultural commodities are produced by private farms and farmers.

[5] We refer readers to Baker et al. (2013) for details of the construction of the EPU series. http://www.policyuncertainty.com

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The remainder of the paper proceeds as follows. Section 2 provides a theoretical framework and review of the relevant literature, sections 3 and 4 describe data and their time series properties respectively, section 5 presents empirical models, identification strategies, results and robustness checks, section 6 discusses the results, and finally section 7 concludes the paper.

1.2 THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Let the Demand and Supply function for an agricultural commodity be

$$Q_{Dt} = Q_D(P_t, Z_{1t}, \varepsilon_{1t})$$

$$Q_{St} = Q_S(P_t, Z_{2t}, \varepsilon_{2t})$$

where, P is the spot price, Z_1 is the vector of demand shifting variables, Z_2 is the vector of supply shifting variables, $\mathcal{E}_1$ and $\mathcal{E}_2$ are random shocks. Let N be the level of inventory. Therefore

$$\Delta N_t = Q_S(P_t, Z_{2t}, \varepsilon_{2t}) - Q_D(P_t, Z_{1t}, \varepsilon_{1t})$$

Rewriting the above equation as an inverse demand function gives

$$P_t = f(\Delta N_t, Z_{1t}, Z_{2t}, \varepsilon_t)$$

which shows price as a function of inventory level, and other demand and supply shifting variables. Inventory levels play a crucial role in determining commodity prices (Krugman, 2011; Pindyck, 2001; Frankel 2014; Kilian and Murphy, 2014). While inventory holdings can change, production in any period does not need to be equal to consumption. As a result, the market-clearing price is determined not only by current production and consumption, but also by changes in inventory holdings. According to Frankel (2014) if the level of inventories is observed to be at the high end historically, then storage costs must be high, absent of any large recent increases in storage capacity. This, in turn, increases supply in the market and exerts a

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downward pressure on the price. Thus, we expect a higher level of inventory to exert downward pressure on commodity price.

Aside from inventory, a number of demand and supply shifting variables are also considered to play important role in commodity price. Frankel (1986, 2008) develop models relating news about US monetary policy such as (unexpected) interest rate changes to commodity prices. According to him high interest rates are expected to reduce the demand for storable commodities, or increase the supply, through the following channels: (1) by increasing the incentive for extraction today rather than tomorrow (for non-renewable commodities), (2) by decreasing firms' desire to carry inventories, (3) by encouraging speculators to shift out of commodity contracts (especially spot contracts). As a consequence of the increase in supply, prices are expected to fall.

The existing literature on the impact of monetary policy on agricultural commodity prices is dominated by the 'overshooting' models that test how agricultural prices change relative to industrial/general price level in response to a monetary policy shock. Frankel (1986) was the first to introduce Dornbusch`s "overshooting" model in the commodity price literature. He distinguishes between fast changing agricultural prices and slow changing industrial prices and demonstrates that monetary change can cause agricultural prices to overshoot their long run equilibrium and, thus, have short-run real effects on agricultural prices. However, Lai et al. (1996) argue that agricultural prices may overshoot their long-run equilibrium level if the monetary changes are unanticipated. Lately, there has been renewed interest in the empirical analysis of the impact of monetary changes on agricultural prices by employing VAR, Co-integration, and Vector Error-correction (VECM) models. Using indexes of different kinds of agricultural prices, they find both in favor of the overshooting hypothesis (Orden et al. 1989,

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Dorfman et al. 1996, Saghaian et al. 2002) and against the hypothesis (Lapp 1990).

There is also a large body of literature that examines the impact of monetary policy on agricultural commodity prices without explicitly testing the 'overshooting' hypothesis. Devadoss (1990) applying 3SLS method shows expansionary monetary policy has positive impact on two indexes of agricultural commodities, while Awokuse (2005) applying a VAR that incorporates 'Directed Acyclic Graph Theory' finds no significant impact of monetary policy on agriculture commodity price. Frankel (2014) considers seven agricultural commodities, among others, and regresses the prices of individual commodities on a set of micro- and macro-economic factors using yearly data from 1960 to 2012. He finds significantly negative effects of real interest rate on the prices of five out of seven agricultural commodities. Applying a structural VAR model on three indexes of food, metal, and industrial inputs, Akram (2009) shows that commodity prices increase significantly in response to a reduction in real interest rates. Anzuini et al. (2013) test the effects of monetary policy shocks on a broad index of commodity prices, and three indexes of metal, food and oil, and show that expansionary U.S. monetary policy shocks drive up the broad commodity price index and all of its components statistically significantly. To investigate the drivers of wheat prices, and quantify their impact, Algieri (2014) estimates a vector error correction model (VECM) and demonstrates the long-run co-integrated relationship between wheat price and four groups of variables namely: market-specific factors, broad macroeconomic determinants, speculative components, and weather. Scrimgeour (2014) applying an event study method on 17 commodities (8 agricultural and 9 metals) shows that a surprise increase in interest rate reduces commodity prices immediately. Employing a cointegrated VAR model, Belke et al. (2014) show that, global liquidity, measured by the ratio of global nominal money to nominal world GDP, is a key driver of the long-run homogeneity of commodity and goods price

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movements. In a recent paper, Hammoudeh et al. (2015) tests the monetary policy shock on a broad index of commodity price and six other sub-indexes. They find a significantly dampening effect of monetary contraction on the aggregate commodity price but with a substantial lag. On the other hand, Ott (2014) regressing a measure of volatility on a number of variables does not find any link between loose monetary policy and commodity price volatility.

While most of the studies use indexes a few studies extract a latent variable called 'common factor' from the prices of a broad group of agricultural and non-agricultural commodities and test the effect of interest rates and other variables on that factor (Vansteenkiste, 2009; Lombardi et al., 2012; Byrne et al., 2013; Poncela et al., 2014). The results from such analyses show both significant and insignificant roles played by monetary policy on commodity price.

Among other macroeconomic variables, global demand is considered to be an important driver of commodity prices. The hey days of the Chinese economy, even during the global financial crisis, are believed to keep the commodity prices high. The literature that emphasizes the role of global demand includes Svensson (2008) and Krugman (2008). US dollar exchange rates are also considered to be an important contributor to the fluctuations of commodity prices as international trades of agricultural commodities are denominated in US dollar. An appreciation of US dollar exchange rates may depress prices by reducing demand (Manera et al. 2013; Mussa 1986; Roache 2010). Oil price may increase agricultural commodity prices by increasing production cost as well as demand for grains as biofuels. Beck (1993), Dixit and Pindyck (1994), and Byrne et al. (2013) also suggest a role for macroeconomic uncertainty in commodity price fluctuations. While uncertainty may depress price by reducing investment, it may also increase price by reducing supply and production. Commodity markets have registered a progressive financialization over time. Such financialization has brought about an increase in

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speculation, which could have positive or negative effects on commodity markets, and consequently on prices (Masters, 2008; Tang and Xiong, 2012).

To capture the financial market condition, in addition to S&P 500 index, we also construct an 'excessive speculation' index following Working (1953). This metrics is a good measure of speculative activities in futures markets, since it assesses the relative importance of speculative positions with respect to hedging positions and indeed as Working (1953) suggested, the level of speculation is meaningful only in comparison with the level of hedging in the market. Formally, the excessive speculative index is given by

$$\text{ESPI}=\left[1+\frac{SS}{(HL+HS)}\right]*100 \quad \text{if } \text{HS}\geq\text{HL}$$

$$\text{ESPI}=\left[1+\frac{SL}{(HL+HS)}\right]*100 \quad \text{if } \text{HL}\geq\text{HS}$$

Where SS and SL are the speculative (non-commercial) short and long open interest respectively, and HS and HL are the hedgers' (commercial) short and long position respectively.

1.3 DATA AND VARIABLES

We consider spot prices of agricultural commodities for our analyses. Monthly series of commodity spot prices are obtained from three sources: United States Department of Agriculture (USDA), the International Monetary Fund (IMF) Primary Commodity Database, and *IndexMundi* (http://www.indexmundi.com/)[6]. Inventory in a period is defined as carried over stock from the previous period plus production in that period minus disappearance (use) in that period. The inventory data for the individual commodities are obtained from USDA, which are updated monthly outlook of ending stocks. We proxy global economic conditions by a series of industrial production which is obtained from CPB Netherlands Bureau for Economic Policy Analysis (http://www.cpb.nl). To check robustness, we also use another measure of global

[6] A list of the commodities is given in the appendix.

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economic activities proposed by Kilian (2009). In order to account for monetary policy, we use the real interest rate of the US which is constructed using the Federal Fund Rate (FFR) and CPI inflation rate. We use US Real Effective Exchange Rates (REER) as the measure of US dollar exchange rates. FFR, CPI and REER series are extracted from FRED of St. Louis FED. To capture macroeconomic uncertainty we use the series ‘Economic Policy Uncertainty’ of the US developed by Baker et al. (2013) (http://www.policyuncertainty.com). In order to account for financial market condition we use S&P 500 index which is obtained from ‘Yahoo finance’. The short and long commercial and non-commercial open interest position data are obtained from the US Commodity Futures Trading Commission (CFTC) (Historical Commitments of Traders reports on futures contracts traded). We also use the West Texas Intermediate (WTI) oil price, and the price of Potassium Chloride as fertilizer price.

All the nominal variables are converted into real terms and all the series except interest rates are in logarithmic form. Further treatment on data for dynamic factor analysis is discussed in section 5.2. The sample period is from 1991m1 to 2014m5[7]. The selection of the sample period is dictated by the availability of data.

1.4 TIME SERIES PROPERTIES AND LAG LENGTH SELECTION

As a preliminary step in our empirical investigation, we test for stationarity of the series involved. The Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) tests suggest that almost all the series are non-stationary at level[8]. Although according to Sims et al. (1990), the SVAR estimates are efficient in the short and medium term even if the variables are non-stationary, following Bernanke et al. (2005) we use the 1st difference of all the series to avoid any spurious relation. Following convention of the literature, we use twelve lags. With monthly

[7] We also use a sub-sample until 2008 to avoid data from the period of financial crisis.
[8] To save space we do not report the test results, however they are available upon request.

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data twelve lags captures one year of dynamics, and is sufficient to eliminate autocorrelation of residuals (Anzuini et al. 2013). However, for robustness check, we also report impulse response functions estimated using lags selected by the Schwarz Information Criterion (SIC).

1.5 EMPIRICAL MODELS AND RESULTS

1.5.1. Individual Commodities

1.5.1.1. The SVAR model

Let us consider the following structural VAR

$$BX_t = C(L)X_t + \varepsilon_t$$

Where X_t is the vector of the variables, B is the matrix of contemporaneous coefficient, C(L) is the coefficient matrix in lags and $\mathcal{E}_t$ is the structural shock. Pre-multiplying both sides by B^{-1} gives

$$X_t = B^{-1}C(L)X_t + B^{-1}\varepsilon_t$$

$$X_t = A(L)X_t + \mu_t$$

where, $A(L) = B^{-1}C(L)$ and $\mu_t = B^{-1}\varepsilon_t$. Our task is to take the observed values of μ_t and to restrict the system so as to recover ε_t as $\mu_t = B^{-1}\varepsilon_t$. Letting the variance–covariance matrix of μ_t be Σ_μ and $\mathcal{E}_t$ be Σ_ε, it can easily be shown that $\Sigma_\mu = B^{-1}\,\Sigma_\varepsilon\,(B^{-1})'$. The left hand side of the equation has n*(n+1)/2 parameters while the right hand side has n*(n+1) free parameters to be estimated. This means that we need n*(n+1)/2 restrictions for the model to be exactly identified. If we normalize the diagonal elements of B to be unity then we will have n*(n-1)/2 additional restrictions to impose for exact identification.

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1.5.1.2 Identification Strategy

The literature on the identification strategy of monetary policy shocks is vast and we do not aim to be exhaustive. Rather, we concentrate on four schemes that somehow stem from different approaches to the issue.

The first identification scheme is based on a recursive (Choleski) identification in the following order of output, monetary policy, inventory, commodity price, REER. The order is based on ‘‘slow to respond’ to ‘fast to respond’’ as mentioned in Bernanke et al. (2005). Here monetary policy follows a Taylor type rule[9] and does not respond contemporaneously to inventory and price of a particular commodity and exchange rates. As pass-through of commodity prices to CPI inflation is low in the US and as FED officially targets core inflation, which by definition excludes fluctuations in food and oil prices, this ordering is justifiable. A look at FED's monetary policy in the recent past further validates our ordering . Moreover, to check if the identified shocks reflect true monetary policy shocks we examine whether the estimated impulse responses of other macroeconomic variables to the monetary policy shock are according to theory, and find them so[10]. A similar identification strategy in commodity price literature is also followed by Akram (2009), Lombardi et al. (2012), Hammoudeh et al. (2015). The identification of our baseline model[11] in a canonical form is as follows:

---

[9] Taylor rule targets output gap and inflation rate. As our monetary policy instrument is real interest rate (FFR deflated by Inflation rate), and all the variables are in real term we do not include inflation explicitly in the model.

[10] To save space we do not report the results here, but they are available upon request.
[11] The selection of the variables in the baseline model is discussed in sub-section 5.1.3

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$$\begin{bmatrix} \epsilon_t^y \\ \epsilon_t^i \\ \epsilon_t^{inv} \\ \epsilon_t^{com} \\ \epsilon_t^{REER} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ g_{21} & 1 & 0 & 0 & 0 \\ g_{31} & g_{32} & 1 & 0 & 0 \\ g_{41} & g_{42} & g_{43} & 1 & 0 \\ g_{51} & g_{52} & g_{53} & g_{54} & 1 \end{bmatrix} \begin{bmatrix} \mu_t^y \\ \mu_t^i \\ \mu_t^{inv} \\ \mu_t^{com} \\ \mu_t^{REER} \end{bmatrix}$$

where y, i, inv, com, REER stand for output, interest rate, inventory, commodity price, and exchange rate. The ordering implies that output is contemporaneously affected by none of the other variables; monetary policy is contemporaneously affected only by output, and so on.

The second identification approach is following Kim (1999)[12], which assumes that monetary policy contemporaneously responds to only commodity prices and exchange rates but not to output and inventories as the measures of the latters are not available within a month. In the commodity price literature Anzuini et al. (2013) follows this identification. In canonical form the identification strategy is as follows-

$$\begin{bmatrix} \epsilon_t^i \\ \epsilon_t^y \\ \epsilon_t^{inv} \\ \epsilon_t^{com} \\ \epsilon_t^{REER} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & g_{14} & g_{15} \\ 0 & 1 & 0 & 0 & 0 \\ g_{31} & g_{32} & 1 & g_{34} & 0 \\ g_{41} & g_{42} & g_{43} & 1 & 0 \\ g_{51} & g_{52} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_t^i \\ \mu_t^y \\ \mu_t^{inv} \\ \mu_t^{com} \\ \mu_t^{REER} \end{bmatrix}$$

[12] Note that some of his variables are different from ours as the focus of their paper is different. We only ensure that our ordering does not violate their ordering-assumptions.

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The third identification strategy is following Christiano et al. (1996,1999)[13], which is a Choleski (recursive) identification in the following order of output, inventory, commodity price, REER, and interest rate. Here it is assumed that monetary policy responds to all of the variables contemporaneously. This identification strategy is also followed by Anzuini et al. (2013) in commodity price literature. The identification scheme in canonical form is as follows-

$$\begin{bmatrix} \epsilon_t^{y} \\ \epsilon_t^{inv} \\ \epsilon_t^{com} \\ \epsilon_t^{REER} \\ \epsilon_t^{i} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ g_{21} & 1 & 0 & 0 & 0 \\ g_{31} & g_{32} & 1 & 0 & 0 \\ g_{41} & g_{42} & g_{43} & 1 & 0 \\ g_{51} & g_{52} & g_{53} & g_{54} & 1 \end{bmatrix} \begin{bmatrix} \mu_t^{y} \\ \mu_t^{inv} \\ \mu_t^{com} \\ \mu_t^{REER} \\ \mu_t^{i} \end{bmatrix}$$

Our fourth identification strategy is following Pesaran and Shin (1998) and is rather an econometric way to avoid the identification debate. The impulse response functions estimated following this method are ‘generalized impulse responses’ which do not depend on ordering of the variables (Pesaran and Shin, 1998). In the commodity price literature Byrne et al. (2013) and Poncela et al. (2014) also follow this identification strategy. Our base line analysis is based on the first identification strategy. We report the findings of the other identification strategies in the robustness check sections.

1.5.1.3 Estimated results

In the base line model we use global demand (proxied by global industrial production), monetary policy (proxied by US real interest rate), physical inventory and price of respective commodity, and US dollar real effective exchange rates. We do not include other variables in the

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[13] As in the previous case, variables are adjusted to be suitable with our case without violating their assumptions on ordering.

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baseline model, as their effects are not significant, and exclusion of them does not affect the results[14]. However, in the robustness checks, we test and report the effectiveness of monetary policy in the presence of the other variables such as oil and fertilizer prices, financial market variables, and macroeconomic uncertainty. Based on the availability of data on inventory, we analyze four commodities namely corn, oat, wheat, and soybean individually. To have a broader indication, first we compute a correlation matrix (Table-1, Appendix B) showing correlation between the prices of four individual commodities and their determinants.

Figure 1, 3, 5 and 7 (Appendix C) show the impulse responses of Corn, Oat, Wheat and Soybean prices respectively to monetary policy and other macroeconomic shocks. From figure 1, 3, 5 and 7 we see that a positive one-standard-deviation shock to global demand (an increase in global demand) increases prices of all the four commodities almost immediately, but the responses become statistically significant with a lag of 6 to 8 months. However, the effects are persistently significant thereafter.

The second box of figure 1, 3, 5 and 7 shows the effect of monetary policy shock on the prices. Because of one standard deviation (30 basis points) contractionary monetary policy shock (an increase in real interest rates) prices of all the commodities fall. Moreover, the effects remain statistically significant for several months. For example, because of a 30 basis points contractionary monetary policy shock, corn price starts falling right from the first month and reaches its minimum at 3% below the base line after 7 months. The price does not go back to its initial level even after 16 months of the shock, though the response becomes statistically insignificant after 1 year. Because of a same magnitude of monetary policy shock, the price of oat falls significantly right from the first month reaching its minimum at 4% below the baseline

[14] Another reason for keeping the baseline model small is to identify our ‘slow-to-fast’ strategy precisely.

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after 6 months. The effect of the shock remains statistically significant for next 15 months. The price of wheat falls from the first month of the monetary policy shock, but the effect of the shock remains statistically significant only for four months. The price of soybean falls significantly from the first month of the monetary policy shock and reaches its minimum at 4% below the baseline after 5 months. The effect of the shock remains statistically significant for 7 months. The third box of figure 1, 3, 5 and 7 shows the effect of the shock to the inventory level. Positive shocks to inventory (an increase in inventory) have a significantly dampening impact on the prices of all the commodities, though the effect disappears quickly in the case of wheat. Moreover, a positive shock to US REER (an appreciation) significantly reduces the commodity prices except for the price of oats.

1.5.1.4 Robustness check

To test the robustness of the effectiveness of monetary policy on individual commodity prices we further estimate six different SVAR models for each commodity. They are (i) For a sub-sample until 2008:8 to avoid the data from the period of financial crisis (ii) For identification based on Kim (1999) (iii) For identification based on Christiano et al. (1996, 1999). (iv) For identification based on Pesaran and Shin (1998) and, (v) including other macroeconomic variables such as oil and fertilizer prices, macroeconomic uncertainty, and the financial market variables. As figures 2, 4, 6 and 8 (Appendix C) show, there are not much variations, from the baseline models, in the impact of monetary policy on individual commodity prices. This implies the robustness of the effect of monetary policy on individual commodity prices.

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1.5.2 Factor Augmented VAR

Due to the unavailability of inventory data for the other commodities, we can't analyze them separately. Instead, we extract a common factor from the prices of fifty agricultural commodities to see how monetary policy and other macroeconomic shocks affect the 'common factor'. This is another way to gauge the effect of monetary policy and other macroeconomic variables in the dynamics of commodity prices[15]. To accomplish this we follow the 'two steps' method proposed by Bernanke et al. (2005). The first step is extracting a factor from the group of variables applying the dynamic factor model (DFM) as below

$$Y_t = \Omega\, F_t + u_t \qquad (1)$$

where, Y_t is n x 1 vector of observed variables which are growth rates of fifty agricultural commodity prices. Ω is the factor loading matrix of order n x k, F_t is the k x 1 vector of common factors and u_t is n x 1 vector of error terms. The second step is to use the factor in a FAVAR model as below

$$\begin{bmatrix} F_t \\ X_t \end{bmatrix} = \Psi(L) \begin{bmatrix} F_{t-1} \\ X_{t-1} \end{bmatrix} + v_t \qquad (2)$$

where, X_t is the m x 1 vector of macroeconomic variables, $\Psi(L)$ is the (p+k) x (p+k) matrix of lag polynomials, v_t is the (p+k) x 1 vector of error terms.

We apply two methods to extract the common factor: principal component and maximum likelihood. Since the number of variables in our analysis is sufficiently large, following Stock

[15] There are at least two reasons why we choose to use 'factor' rather than index. First, the 'factor' is different from index (Byrne et al. 2013, Deaton 1999); second factor analysis gives an idea about the extent of co-movement of the commodities.

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and Watson (2011), we first extract the common factor by principal component[16]. With this, we assume that the weighted averages of the idiosyncratic disturbances will converge to zero by the weak law of large numbers, so linear combinations of the observed series are consistent estimators of the common factors. Consistency of the static principal component estimators has been demonstrated by Stock and Watson (2002) when both the number of series 'n' and the time dimension 't' converge to infinity. Due to this consistency result, we treat F_t as observed for inference purposes.

We also apply maximum likelihood (MLE) method to obtain the common factor, where we model the variables in equation (1) as linear functions of an unobserved factor that follows a second-order autoregressive process. The parameters are first estimated by maximum likelihood method and then efficient estimates of the factors are obtained applying the Kalman Filter. In the robustness check section we report the response of the 'MLE factor' to monetary policy shock.

We extract common factor for the entire sample period, i.e. 1991-2014, as well as for three other sub-samples. The sub-samples are 1991-2008, 1991-2002, and 2003-2014. We identify the factor structure using the parsimonious information criteria proposed by Bai and Ng (2002). Bai and Ng (2002) suggest three penalty functions to be taken into account for principal component estimation. In our case the first two criteria suggest two factors while the third criterion suggests one factor. As most of the commodities are loaded in the 1st factor, for the convenience of further application, we decide to retain one factor[17]. Prices of all the fifty commodities are

[16] Accurately speaking this is 'static form of DFM' unless the number of static and dynamic factors is the same in which case static and dynamic factor models are equivalent (Stock and Watson 2002, 2005).

[17] Byrne et al. (2013), Poncela et al. (2014), and Vansteenkiste (2009) also use one factor for 24, 40 and 32 commodity prices respectively.

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converted in real terms and in logarithmic form. They are also 1st differenced (to make stationary) and standardized before applying dynamic factor models to extract common factors. Table 2 (Appendix D) reports factor loadings which imply percentage of the variance of the change of the price of each commodity explained by the common factor. For example, for Barley the factor loading for the period 1991:1 to 2014:5 is 0.23. This means 23 percent of the variance of the change of the real price of Barley is explained by the common factor. Out of the 50 agricultural commodities, we report only those with factor loadings above 0.10 for at least one of the sample periods. There are several points to make from this table. First, half of the commodities have factor loadings of 0.10 or more. Second, a good number of 'less-traded non-major' commodities such as palm oil and sorghum, which are overlooked in the literature, also co-move with others. This may provide new insights into the importance of macroeconomic variables in commodity price dynamics. The third and most important point is about the trend of the co-movement. Clearly, in the sub-period 2003-2014, there are more commodities with loadings above 0.10, which may imply, in turn, that co-movement is a recent phenomenon or at least stronger in recent time. However, a careful look at the table reveals that for most of the major agricultural commodities the share of common variance is significant even before 2003. Therefore, we cannot say confidently that co-movement is a recent phenomenon, at least for the major agricultural commodities.

Our next task is to use the common factor in a FAVAR model to see the response of the factor to various macroeconomic shocks. We estimate the baseline model with global demand, monetary policy, 'common factor', WTI crude oil price, uncertainty, and REER in this order. In the baseline model we do not include other variables such as S&P 500 index and fertilizer prices as they are not significant and their exclusion does not affect the rest of the results. However, in

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the robustness check, we report results considering other variables and identifications as well. Figure 9 (Appendix E) shows that global demand has significantly positive effect on the common factor. Because of a positive shock (an increase) to global demand, the factor rises right from the second month. The effect becomes statistically significant after four months and remains so until 15th month. Due to one-standard-deviation contractionary monetary policy shock (a 30 basis points increase in real interest rate), the common factor falls right from the first month. The effect becomes statistically significant after 3 months and remain significant for almost a year. The oil price does not have significant impact on the common factor. Therefore, any co-movement of oil price with other commodity prices might be a correlation, not causal relation. Macroeconomic uncertainty also does not have any significant impact on the common factor. Finally, US dollar REER has significant impact on the common factor of the agricultural commodity prices. As US dollar REER appreciates, the common factor of the commodity prices falls significantly.

Figure 10 (Appendix E) shows the impulse responses of the robustness tests of the impact of monetary policy on the common factor. To test robustness, we estimate nine different FAVAR models: for a sub-sample until 2008:8, for an identification following Kim (1999)[18], for an identification following Christiano et al. (1996, 1999), for an identification following Pesaran and Shin (1998), including other macroeconomic variables such as fertilizer price and financial market variables, following lag length based on SIC, using MLE factor instead of principal component factor, using a sub-sample after 2003, and using an alternative measure for global demand proposed by Kilian (2009). As is seen from figure 10, the results confirm the robustness of the effect of monetary policy on the common factor of the agricultural commodity prices.

[18] For these identifications we follow the same assumptions as we do for individual commodities. The identifications in matrix forms are available upon request.

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1.6 DISCUSSION OF THE RESULTS

Structural VAR analysis of individual commodities and FAVAR analysis of the common factor show that, in addition to global demand and US dollar exchange rates, monetary policy plays an important role in the dynamics of the agricultural commodity prices. In particular a 30 basis points contractionary monetary policy shock reduces price of individual commodities to a maximum 2% to 4% below the base line after 4 to 6 months of the shock. Anzuini et al. (2013) find an increase to a maximum of 6% in a broad index of commodity prices as well as in a food index due to 100 basis points easing of monetary policy. Despite the fact that Anzuini et al. (2013) use nominal variables to see the impact on indexes and we use real variables to see the impact on individual commodities, our impulse response functions mostly conform to those of Anzuini et al. (2013). Moreover, like in Anzuini et al. (2013), in our analysis the responses are, while significant and sizeable, not 'overwhelmingly' large. We attribute the difference in the magnitude of impulse responses between us and Anzuini et al. (2013) to the aforementioned dissimilarities and to the introduction of 'inventory' in the analysis. Furthermore, the asymmetric responses of the commodities to shocks justify the individual analysis of the commodities, and imply a significant value addition to the findings of the studies that use indexes. Our results also conform to the findings of a recent study by Hammooudeh et al. (2015), who, like Anzuini et al. (2013), uses a broad commodity index and other sub-indexes of fuel, metal and food commodity, and concludes that a contractionary shock to the US monetary policy reduces the commodity prices significantly. However, unlike Hammooudeh et al. (2015), Anzuini et al.(2013) and we do not find any initial 'pop' (an initial increase in commodity prices due to a contractionary monetary policy shock) in impulse response functions. This initial 'pop' also contradicts the findings of Scrimgeour (2014), who, applying an event study method, shows that a 10 basis

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points increase in interest rates would cause commodity prices to fall by approximately 0.5% immediately. Like Scrimgeour (2014) we also find an immediate fall of commodity prices due to a contractionary monetary policy shock[19].

The estimated impulse response functions from FAVAR models are consistent, in terms of shape and magnitude, with those from similar studies that apply FAVAR in commodity price literature though our focus is different from theirs (Byrne et al. 2013, Lombardi et al. 2012). In the extended literature on commodity prices, our findings of the role of monetary policy are also consistent with the findings of Frankel (2014) and Algieri (2014) who emphasize the role of monetary policy in the long-run development of commodity price.

In addition, consistent with Svensson (2008), Krugman (2008), and Frankel (2014) we find a significant effect of global demand and inventory, and consistent with Manera et al. (2013) and Roache (2010) we find a significant role of US dollar exchange rate in the dynamics of agricultural commodity prices. These findings demonstrate a strong demand-side role in commodity price dynamics. However, unlike Masters (2008) and Tang and Xiong (2012) we find insignificant effect of financial market variables on the dynamics of agricultural commodity prices. Because of the nature and frequency of trades in financial markets and their complex relation with commodity prices, the effect of financialization and speculation deserves to be studied more rigorously which in turn deserves separate analysis. Moreover, unlike Byrne et al. (2013), we do not find a significantly dampening impact of uncertainty on commodity prices. Our finding is justified by the high commodity price amidst the extreme uncertainty during recent financial crisis. Though the absence of causality that runs from oil price to agricultural

[19] With the exception of the case where we follow the third (Christiano et al. 1996, 1999) identification. In this identification, we stop the immediate response of commodity price to monetary policy shock by identification- design, and, as a result, the immediate response is zero.

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price is surprising, it is not uncommon in literature (Lombardi et al., 2012) and might be an indication of the declining trend of oil-intensity in production of agricultural commodities.

1.7 CONCLUSION

Monetary policy in the developed countries has been extraordinarily easy for more than a decade or so, thanks to the internal policies of the economies and global savings glut (Bernanke 2005). During this period commodity prices have also registered substantial increase in level and volatility. In this study, we analyze how monetary policy and other macroeconomic shocks affect the dynamics of agricultural commodity prices. First, we analyze four individual commodities, namely corn, wheat, oat and soybean, separately in structural VAR framework. Analysis of the commodities individually allows us to control for their respective inventory levels, considered to be an important determinant of commodity prices. Second from a large number of agricultural commodity prices we extract a common factor to test the impact of monetary and macroeconomic shocks on the common factor. The structural and factor-augmented VAR analyses show that monetary policy, in addition to global economic conditions and US dollar exchange rates, significantly affects the price dynamics of the agricultural commodities. Moreover, the factor analysis reveals that more commodities (including some less traded ones) have been co-moving since 2003, though the co-movement in major agricultural commodities is pronounced even before 2003. To summarize, our results confirm the relevance of the real interest rate for agricultural commodity prices, and they are consistent with the view that monetary easing may lead to higher commodity prices.

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CHAPTER 2

WAL-MART AND PRICE CONVERGENCE AMONG US CITIES

2.1 INTRODUCTION

In this paper we examine the role played by Wal-Mart on the price convergence in the cities in the U.S.A. Wal-Mart is the largest retail store in the world and its market share is also the largest in the US retail trade sector. Wal-Mart is the largest private sector employer in the world and its 2005 revenues exceeded those of the next five U.S. retailers combined (Schulz 2006 as mentioned in Basker 2007). While it is a popular destination for shoppers seeking lower prices and varieties of goods under one shed[20], it suffers the wrath of groups fighting to preserve small town main streets (mom and pop stores) and those trying to unionize workers. As it has become a serious policy issue whether to allow Wal-Mart in the city or not, and whether to intervene in Wal-Mart's business strategy or not, it is not surprising that Wal-Mart has drawn considerable attention from the academics.

A number of studies examine the effects of Wal-Mart on various economic and social indicators that range from price to wage, obesity to crime, inequality to competition. Basker (2005b) tests the price effect of Wal-Mart entry on ten non-grocery items and finds that Wal-Mart reduces the prices of almost all the items with detergent, shampoo, and tooth paste even statistically significantly. Hausman and Leibtag (2007) show that Wal-Mart supercenters have big impact on retail price of food, as they offer groceries at 15%–25% lower than traditional supermarkets. Basker and Noel (2009) estimate a short-run 1–2 percent price reduction by

[20] Phone surveys suggest that 84% of households in the U.S. shop at Wal-Mart in a given year with 42% of households reporting to be regular Wal-Mart shoppers (Pew Research Center, 2005 as mentioned in Pope and Pope (2015)).

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competing grocery stores due to Wal-Mart's entry, whereas Glandon and Jaremski (2014) show that individual stores offer more discounts as the distance to Wal-Mart falls.[21]

A closer look at the retail trade sector in the United States reveal that there is a growing tendency towards market consolidation in recent decade (Pope and Pope 2015, Ellickson and Grieco 2013). Information technology, modern management techniques, improved supply chain management, and improvement of transportation infrastructure are among the crucial factors leading to these consolidations (Ellickson and Grieco 2013). Similar changes also have been taking place in Europe, Japan, and even in China and India (Fernie et al. 2009, Gielens et al. 2008, Igan and Suzuki, 2012).

Consequently, big box stores like Wal-Mart, Kroger, and others have increased in numbers and coverage of population (Pope and Pope 2015). The huge market power of a few large corporations in both end of the product (producers and consumers) surely will have impact on price charged by these companies which would ultimately affect the prices of the commodities in the local markets they serve. Thus it is imperative to ask whether these additions of big box stores like Wal-Mart affects the extent of price convergence in the retail markets. Although Wal-Mart stores have been around for a while and have influenced prices of goods and services for decades in the retail sector in the USA (Basker, 2005b; Hausman and Leibtag, 2007; Basker and Noel, 2009), there exists virtually no study to examine the effects of Wal-Mart or other big-box chain-stores on price convergence. This paper is an attempt to fill this gap by examining how the remarkable change in US retail architecture over the last two decades has affected market integration in the US cities by examining the role of Wal-Mart to city price

[21] Other studies on the effect of Wal-Mart include but not limited to Basker (2005a) and Neumark et al. (2005) on labor market, Pope and Pope (2015) on land price, Wolfe and Pyrooz (2014) on crime.

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convergence. The rate of convergence/divergence may turn out to be a crucial variable in determining the welfare impact of Wal-Mart as faster price convergence reduces misallocation of resources and thereby increases welfare.

There exist considerable challenges to pin point the impact of Wal-Mart on price convergence in U.S. cities. On the one hand we have issues related to obtaining reliable data and on the other hand, we need to have a sound identification scheme to apprise the role played by the Wal-Mart. On the data issues, first, we need a large panel data on retail prices at many locations in the U.S. and second, we need to construct a variable that represents the presence/absence of Wal-Mart at those locations at a particular time period, and third we need a large number of location specific data such as rent and wages. In respect of identification scheme, it is crucial to understand how the presence/absence of Wal-Mart in the retail sectors can influence the price convergence in U.S. cities.

Fortunately, in respect of data issues we find that American Chamber of Commerce Research Association has been collecting quarterly city price data for more than 200 cities for 50 consumer items from 1980. Holmes (2011) has compiled data on location and opening/conversion of Wal-Mart for the period 1990-2006. In order to explore recent data, one has to extend Holmes' (2011) data set. It turns out that to extend the database on Wal-Mart opening/conversion one has to go through all the press releases from Wal-Mart's news archive for the period 2007-2014. Although it was a daunting task, yet it provided an opportunity to extend the database. Location specific data are available from different government sources like Bureau of Economic Analysis (BEA) and U.S. Census. Thus, with significant efforts, a workable database can be constructed and we have accomplished this feat.

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Our identification strategy can be summarized in the following ways. First, it is empirically established that the presence of Wal-Mart in a local market reduces retail prices of goods and services at that location (Basker 2005b, 2007; Hausman and Leibtag 2004, 2007). Second, it can be argued that the prices of goods and services at two Wal-Mart stores at two cities would be closer than those for two independent retail stores at those two cities since wholesale prices and many other costs as well as mark-ups are likely to be more similar for two Wal-Mart stores. Consequently, one would expect prices to be closer in two cities if both of them have Wal-Mart than if none or only one of them has Wal-Mart. Therefore, to capture the Wal-Mart effect on price convergence we construct a variable representing the existence of Wal-Mart in a city at a particular period.

Using quarterly prices of 24 products in 101 cities in the U.S.A. over 25 years and controlling distance, wage, rent, and city and time specific fixed effects we show that prices are significantly closer in two cities if both of them have Wal-Mart than if none or only one of them has Wal-Mart. Moreover, Wal-Mart's effect is more pronounced for grocery items than non-grocery items, and within high income cities than within low income cities. Our regional analysis further reveals that Wal-Mart helps inter-region price convergence more than intra-region price convergence.

Major contributions of our study are two-folds. First, it proposes a new avenue to consider when analyzing the factors responsible for price convergence or divergence. Despite the importance of market structure, and the fact that US retail architecture has massively changed over last two decades, the role played by rapidly-expanding big-box stores in price convergence is completely over-looked in the literature. We attempt to fill this gap. Second, our study adds to the literature of the socio-economic effects of Wal-Mart. As there are growing concerns about

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whether to allow Wal-Mart in the town or not, whether to intervene in Wal-Mart's business strategy or not, our study provides new information for policy makers in this regard.

The remaining of the paper proceeds as follows. In Section 2 we discuss briefly the existent literature on price convergence and propose a theoretical explanation of the role of Wal-Mart in the functioning of LOP. Section 3 describes data and variables. In section 4 we construct and discuss the measures of price dispersion. In section 5 we carry out empirical analysis to test the impact of Wal-Mart on the cross-city price dispersion. In section 6 we check the robustness of our findings. Section 7 provides the findings from regional analysis. Section 8 reports results on Wal-Mart's impact on the price convergence of services. Section 9 provides discussion and economic implication of the findings. Finally, we conclude in section 10.

2.2. PRICE CONVERGENCE AND THE ROLE OF WAL-MART IN PRICE CONVERGENCE

2.2.1 Price convergence

The law of one price (LOP) suggests that the prices of the same good should not be different at different locations once transaction and transportation costs are taken into account. Testing the validity of LOP is of great interest to economists as its failure constitutes the failure of purchasing power parity and causes welfare losses (Engel and Rogers 2001). However, despite applying the modern econometric techniques and using longer span of data, empirical studies still find a significant deviation from the law of one price.

The literature provides several explanations for the failure of law of one price. One strand of literature tests the law of one price across borders contrasting relative price patterns within and across countries. Engel and Rogers (1996) using disaggregate city price data of USA and Canada show that relative prices of cross border city pairs are much higher than that of

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within-country city pairs. They call it 'border effect'. A number of subsequent studies also confirm the existence of 'border effect' (see, Parseley and Wei 2001, Haskel and Wolf 2001, Gopinath et al. 2011, Morshed 2003). They attribute this failure to the existence of transaction costs which may arise from various reasons including tariff and non-tariff barriers, the failure of nominal exchange rates to adjust to relative price shocks, segmented markets, sticky nominal prices and transportation costs[22].

Another strand of literature examines price convergence among the cities within a country. This approach provides a more controlled environment, as problems due to fluctuations in exchange rate, tariff and non-tariff barriers, or factor market rigidities are eliminated. Using data from US cities, Parsley and Wei (1996), Crucini and Shintani (2008), and Yazgan and Yilmazkuday (2011) show that speed of price convergence is significantly faster than that across countries[23]. Though, the convergence rate is faster within a country than across countries, the slow rate of convergence still remains a puzzle. In the literature a number of factors are considered to be responsible for the slow convergence. These are pricing to market or differential mark-up (Haskel and Wolf 2001, Lutz 2004), transportation costs and sticky nominal prices (Engel and Rogers 2001), local non-traded retailing cost or pricing to market at the retail level (Burstein et al. 2005), tradability, non-traded factors of production and the competitive structure of the markets (Crucini et al. 2005), and geographical barrier (Kano et al. 2013).

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[22] A slightly different strand of literature also tests if economic integration of the countries reduces price dispersion. Goldberg and Verboven (2005), and Ogrokhina (2015) show that European market integration process (1970-2000) and Single European Act (SEA) positively affect the price convergence process while Engel and Rogers (2000) find a large border effect even during NAFTA era. Moreover, Engel and Rogers (2004), Parsley and Wei (2008), Ogrokhina (2015) fail to find any converging effect of a single currency such as Euro.

[23] In a sharp contrast Cecchetti et al. (2002), find a much larger half-life figure (9 years) by using consumer price indices of U.S cities.

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2.2.2 The role of Wal-Mart in price convergence

We decompose the final retail price of product k in city i into its various components following Harrod (1939), Engel et al. (1996), and Haskel and Wolf (2001) in the following way

$$P^{ki} = \left(f^{ki}\right)^{\alpha}\left(c^{i}\right)^{1-\alpha}\left(1 + T^{i}\right)m^{ki} \qquad (1)$$

where P^{ki} is the retail price of goods/service k at locale i, f^{ki} is the wholesale cost, c^{i} is the local non-traded input cost (including transportation cost), T^{i} is the local sales tax rate, and m^{ki} is the mark-up.

Therefore, taking log of the relative price of good k at two locations i and j yields

$$\ln\left(\frac{P^{ki}}{P^{kj}}\right) = \alpha \ln\left(\frac{f^{ki}}{f^{kj}}\right) + (1-\alpha) \ln \left(\frac{c^{i}}{c^{j}}\right) + \ln\left(\frac{(1+T^{i})}{(1+T^{j})}\right) + \ln\left(\frac{m^{ki}}{m^{kj}}\right) \qquad (2)$$

A simple first explanation, of course, attributes price difference to costs of arbitrage, most importantly to transportation cost (Kano and Kano 2013). Apart from that, the cost of a retail product is the combination of wholesale cost and local wage and rental cost plus sales tax. The wholesale costs of the products are generally not publicly available and one would expect that rental cost, local wage and sales tax would affect all stores in the same way. The potential asymmetry of wholesale prices of different goods for different stores would be crucial to identify the impact of big box stores on price convergence. One of the main characteristics of big box stores like Wal-Mart is that many nearby stores get products from the same distribution center and thus face the same wholesale price. This opened the avenue to examine the role to Wal-Mart on price convergence at different locations.

As a matter of fact the wholesale cost of two Wal-Mart stores in two nearby cities are likely to be more similar than two independent stores locating in that two cities. Usually a large number of

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Wal-Mart stores (around 100) get their supply from a single hub (called distribution center)[24] (Wal-Mart, 2016). If two stores get their supply from same distribution center, basically it implies that both the stores have same wholesale cost (of course the transportation cost from the distribution center to stores may vary). This feature, along with the fact that Wal-Mart does not depend much on intermediaries (Wal-Mart, 2016), reduces the wholesale-cost asymmetry among its stores significantly.

At the retail level, Wal-Mart's ‘proprietary retail link software’ provides it with a tremendous advantage in logistics and inventory control. Wal-Mart's efficiency gains were the source of 25 percent of the entire U.S. economy's productivity improvement from 1995 to 1999 (Singh et al. 2009). Access to the same technology of inventory management and customer services by all the Wal-Mart stores further reduces the cost-asymmetry at the retail level among the stores. In fact, a study using a ‘very large chain store’ data by Gopinath et al. (2011) argues that retail prices in a store respond significantly to changes in costs in neighboring stores (within a country). Though local specific costs such as wage, rent and sales tax should affect Wal-Mart and other stores equally, we control for them in our analysis in case they vary across stores.

Markup is another important contributor to the asymmetries of the prices. Markup varies from product to product, and place to place. The extent of markup depends on the demand structure of a particular product in a particular city, level of competition and the retailer’s business strategy. Data on markup are not publicly available. However, it is likely that, for a product, markup is more similar between two Wal-Mart stores, than between two independent stores given other conditions are same. There are several reasons for that. Unlike other groceries, which follow ‘Hi-Lo’ or ‘promotional’ pricing strategy, Wal-Mart follows ‘Every Day Low

[24] Drugs are exceptions, which are directly supplied to the stores.

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Price' business strategy[25] which requires a proportionate mark-up on each commodity. Such stable and low mark-up policy, should reduce the markup-asymmetries among its stores. Moreover, even if each store sets its own price depending on local market condition, the pricing policy for Wal-Mart must conform to the established policy guidelines of the central management. A centralized decision making for a number of stores should possibly induce similarity in the mark-ups[26]. The increasing prevalence of online sales by online retailers including Wal-Mart reduces the search cost for the customers and make it harder for Wal-Mart to differentiate prices, significantly, across its stores.

As the wholesale cost and markup are likely to be more similar between two Wal-Mart stores than two independent stores, the retail prices are likely to be more similar between two Wal-Mart stores than between two independent stores. Since it is established in the literature, and we also find, that Wal-Mart has significant impact on lowering the prices in the cities it operates in (Basker 2005b, 2007; Hausman et al. 2004, 2007, Basker and Noel 2009), it is expected that two cities with Wal-Mart have more similar prices than the two cities without Wal-Mart. Therefore, our hypothesis is: prices are significantly closer in two cities if they have Wal-Mart than that if none or only one of them has Wal-Mart.

2.3 DATA

To assess the effects of Wal-Mart on price convergence, we collected quarterly data on retail prices at many different locations as well as location specific data on wages and rent. We

[25] As 'Everyday low price' strategy is a proven business strategy for Wal-Mart (Deisha Barnett, 2015, a Wal-Mart spokeswoman) it is likely that they don't deviate from it. (Source: 'Wal-Mart ratchets up pressure on suppliers to cut price', *The Wall street journal*. website: http://www.wsj.com/articles/wal-mart-ratchets-up-pressure-on-suppliers-to-cut-prices-1427845404).

[26] Wal-Mart not only sells a number of products online but also has recently started matching all the prices of the products sold online by websites such as Amazon within Wal-Mart stores (Wal-Mart 2015).

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also collected detailed data about opening/conversion dates of Wal-Mart discount stores and Supercenters at those locations. More details of the data and data compilation process are given below.

2.3.1 Retail Prices

Data on grocery and non-grocery prices are obtained from the American Chamber of Commerce Research Association's quarterly *Cost of Living Index*[27]. In constructing the index, ACCRA relies on unweighted average prices from cities around the country gathered by local chambers of commerce on a quarterly basis. ACCRA designs the *Cost of Living Index* to be a measure of the cost of living for a mid-management household and, as such, advises its price collectors to *"Select only establishments where individuals from professional and managerial classes would normally shop. Even if discount stores are a majority of your overall market, they shouldn't be in your sample at all unless upper-income professionals and executives really shop there''.*[28]

As a result, these data are likely to reveal the lower bound of "Wal-Mart Effect" on price convergence. The number of cities included in the ACCRA sample fluctuates from quarter to quarter[29]. Of these, we select 101 cities from contiguous USA for which data from at least 90 quarters are available. Table 1 provides some summary statistics of the sample cities.

[27] A number of recent papers used this database such as O'Connell and Wei (2002) and Parsley and Wei (1996).
[28] American Chamber of Commerce Research Association. *Cost of Living Index Manual*. December 2005. p.1.2.http://www.coli.org/surveyforms/colimanual.pdf, ACCRA data are collected before sales tax are added to prices.
[29] Besley and Rosen (1999) explain that inclusion or exclusion of a city in a certain quarter do not bring any bias in sample.

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Table 2.1: Sample city summary statistics

Mean Population (2010 census)	2,77,249
Mean household income in 2013 Inflation adjusted dollar	60,544
Percentage of cities in South	48% (48)
Percentage of cities in Midwest	29% (29)
Percentage of cities in West	19% (19)
Percentage of cities in Northeast	4% (5)

Note: Sources of population and income data are from American Fact Finder (http://factfinder.census.gov). The regional classification is based on US Census Bureau. No of cities are given in the parentheses.

Table 2.1 reveals that our criteria for selecting cities with at least 90 quarters of data yields a large chunk of the cities in the South while only a few cities from the Northeast. Since we are interested about price convergence, we need data for a longer time span. We understand that this geographic asymmetry in city locations would be a potential concern about generality, but similar restrictions are also imposed by Parsley and Wei (1996) who used data for only 44 cities and half of them were Southern cities. O'Connell and Wei (2002) used data only for 20 cities and those are mainly cities from the South and Midwest. Our sample includes almost all the cities considered in their analyses. Most importantly, our sample of cities closely resemble the expansion of Wal-Mart stores.

The prices collected by ACCRA cover both goods and services. From the list, our selection of goods is limited to those items consistently available in the ACCRA survey during the period of our study. After excluding, we are left with six non-grocery items[30] and 18 grocery

[30] Basker (2005) considers 10 non-grocery items of which we exclude aspirin, cigarettes, pants and underwear as all of these are discontinued from 2003.

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items. We use quarterly prices of the 24 products[31] in 101 cities over 25 years, from 1990 to 2014. 101 cities form 5050 city pairs ((101*100)/2)-each with up to 100 quarterly observations. Thus the sample consists of a maximum 505000 (5050*100) observations of price dispersions among the city pairs.

2.3.2 Wal-Mart stores

We consider two types of Wal-Mart stores: Wal-Mart Discount Stores and Wal-Mart Supercenters[32]. Wal-Mart's website distinguishes between Wal-Mart (discount) store and Supercenter as

"*Smaller than a Supercenter, discount stores employ about 200 associates and offer electronics, apparel, toys, home furnishings, health and beauty aids, hardware and more in about 106,000 square feet of open, brightly lit space. Wal-Mart Supercenters offer a one-stop shopping experience for electronics, apparel, toys and home furnishings with the added convenience of a grocery store with fresh produce, bakery, deli and meat and dairy products.*[33]*"*

Furthermore, a report of Wall street journal goes as

"……. the (supercenters) offer both merchandise and groceries… … The (discount stores) typically don't offer groceries[34]*".*

Previous studies such as, Basker (2005b) when analyzing the impact of Wal-Mart on non-grocery items consider Wal-Mart discount stores, and Basker and Noel (2009) when assessing Wal-Mart's effect on grocery items consider Wal-Mart Supercenters. Therefore, in line with

[31] A complete list of the grocery and non-grocery items and their definitions is given in the appendix.

[32] We avoid Sam's club from our study as they are not directly substitute for traditional groceries.

[33] http://corporate.walmart.com/our-story/our-business/walmart-us)

[34] Wal-Mart Now Has Six Types of Stores; Wall street journal, http://247wallst.com/retail/2014/03/22/walmart-now-has-six-types-of-stores.

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Wal-Mart's own definition and previous researches, to see Wal-Mart's effect on price convergence we use the opening-dates of Wal-Mart (discount) stores for non-grocery items, and the opening/conversion-dates of Wal-Mart supercenters for grocery items.

Entry of Wal-Mart Supercenter can come through two channels: a new store can be opened as a Supercenter or, alternatively, an existing Wal-Mart discount store can be converted to the Supercenter. For locations and opening/conversion date of Wal-Mart stores and supercenters, we extend the dataset constructed by Holmes (2011) for the period of 1990 – 2006 to 2014. For data since 2006, we meticulously collected data from the press releases about the new openings or conversions in the news archives section of Wal-Mart's website[35]. Around 80% of the cities have Wal-Mart discount store opened during the first half of our sample (i.e. before 2003) whereas around 60% of the cities have Wal-Mart Supercenters opened/converted during the first half of our sample.

2.3.3 Other data

We also collected data for local costs such as rental prices and wages as they influence the retail prices. The lack of available data on city specific commercial rents forces us to use residential rents in the cities, in this case we use housing price (rent of a 3-bed room apartment) published in the ACCRA survey. For wage rate we use state level minimum wage data that are obtained from the website of United States Department of Labor[36].

It is important to include a variable that represents costs of arbitrage in a research on price convergence and most of the researchers suggested the distance between locations as an

[35] Website: http://news.walmart.com/news-archive. A contact with Wal-Mart for data was not successful.
[36] Website: http://www.dol.gov/whd/state/stateMinWageHis.htm. Where there is no state minimum wage we use the FLSA (Fair labor standards act) minimum wage which is applicable for all private, federal, state and local government employee.

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imperfect but necessary proxy for that (Kano and Kano, 2013). We used the distance between two locations as driving distance (of 5050 city pairs) collected from the website distanceonline.com.

2.4. MEASURING PRICE DISPERSION AND CONSTRUCTION OF WAL-MART VARIABLE

2.4. 1 Measuring Price Dispersion

One of our goals is to estimate the influence of Wal-Mart on the size of the deviations from the LOP. Accordingly, following Bergin and Glick (2007) and Engel et al. (2003), relative log prices of a commodity of all city pairs are constructed. More specifically let $p^{k}_{i,t}$ be the log of price of k in city i at time t. For a given pair of cities (i,j), the relative price for a given good and time is,

$$q^{k}_{ij,t} = p^{k}_{i,t} - p^{k}_{j,t} \tag{3}$$

Let define the average price dispersion at time t for the city pair (i,j) as the mean square error of $q^{k}_{ij,t}$ across all products k:

$$MSE_{ij,t} = \sum_{k \in K} \left(q^{k}_{ij,t}\right)^{2} / K_{\mathrm{T}} \tag{4}$$

Where K is the set of products and K_T is the total number of products. However we also construct two other measures and report the results using these measures in the robustness check section. First, following Parsley and Wei (2001, 2002?) we construct Demeaned-MSE (DMSE) in the following way.

$$DMSE_{ij,t} = \sum_{k \in K} \left(q^{k}_{ij,t} - q^{\underline{k}}_{ij,\ \ t}\right)^{2} / K_{\mathrm{T}} \tag{5}$$

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Where, $q^k_{\overline{ij},\ t} = \sum_{ij\in C} q^k_{ij,t} / C_T$, and C_T is the set of city pairs. This measure controls for the possibility that the magnitude of the deviation from the law-of- one price may depend on the type of the product, by removing the mean of the price gap for each good across all city pairs. Second, following Bergin and Glick (2007), we also construct Mean Absolute Difference (MAD) in the following way,

$$MAD_{ij,t} = \sum_{k\in K} \left| q^k_{ij,t} \right| \ / \ K_T \qquad (6)$$

2.4. 2. Construction of Wal-Mart Variable

Using our data on presence and absence of Wal-Mart at a particular city, we followed the following procedure to construct a dummy variable for city pairs. For each quarter and each city pairs, if we have Wal-Mart at both cities the dummy variable assumes 1, and 0, otherwise. This implies even if in a city pair, there exists a Wal-Mart in one of the two cities, the dummy would assume 0. This is consistent with our identification strategy as presence of Wal-Mart in one location may reduce the prices at that location but the absence of Wal-Mart in the other city will have no similar effect and thus the presence of Wal-Mart in one city in city pairs will have potentially no or diverging effect on price convergence[37]. About 75% of the value of Wal-Mart dummy is 1 for Wal-Mart discount stores, and 46% of the values of Wal-Mart dummy is 1 for Wal-Mart supercenters. This implies that the Wal-Mart variable has sufficient variation to pick up the Wal-Mart effect.

2.5. EMPIRICAL RESULTS

2.5.1 Effects of Wal-Mart on price level

[37] In robustness check section we compare between the three scenarios (both, one and none of the cities in the pair have Wal-Mart). The results conform to our primary finding.

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Since a crucial component of our identification strategy is the effect of Wal-Mart on local price level, following Basker (2005b) we first estimate the following equation to see the effect of Wal-Mart on the prices in our sample:

$$p_{kjt} = \alpha_k + \beta_k p_{kj,t-1} + \theta_k\, WM_{jt} + \sum_j \gamma_{kj}\, city_j + \sum_t \delta_{kt}\, quarter_t + \sum_j \tau_{kj}\, trend_t + \varepsilon_{kjt} \quad 7$$

where p_{kjt} is the natural log of the price of product k in city j in quarter t, $quarter_t$ is a quarter indicator , $city_j$ is a city indicator, $trend_t$ is a linear trend and WM_{jt} is the Wal-Mart indicator: it equals 1 if city *j* has a Wal-Mart in quarter *t*, otherwise 0. The results of this regression are reported in Table 2.2. We find negative coefficients of Wal-Mart indicator for all the grocery items and nine of them are significant at at least 10% error probability level. For non-grocery items four out of six commodities yield negative coefficients with detergent and shampoo yield significant negative coefficients. Only coke yields a positive but significant coefficient. These results indicate that the presence of Wal-Mart Super Center or Wal-Mart Discount stores reduces the price of these commodities. Thus, these results, along with the findings of Basker (2005b), Hausman et al. (2007), Basker and Noel (2009), support an important facet of our identification strategy.

Table 2.2: Effects of Wal-Mart on commodity prices.

Grocery Items		Non-Grocery Items	
Banana	-.0210***	Coke	.0196*
Beef	-.0090	Detergent	-.0098**
Bread	-.0248***	Facial tissue	-.0010
Cheese	-.0014	Shampoo	-.0141*
Chicken	-.0123*	Shirt	.0092
Coffee	-.0023	Tooth paste	-.0007
Corn	-.0124*		
Cornflakes	-.0167***		
Eggs	-.0173***		
Lettuce	-.0024		
Margarine	-.0055		

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Table 2.2: Effects of Wal-Mart on commodity prices(Continued)

Milk	-.0045*		
Peaches	-.0025		
Potato	-.0005		
Steak	-.0158***		
Sugar	-.0040		
Sweet peas	-.0065		
Tuna	-.0154***		

Note: Dependent variable is the ln of price. The values are the coefficients of Wal-Mart (WM) variable in equation (7). The WM variable is a dummy taking 1 if there is a Wal-Mart in the city at that period, otherwise 0. For grocery items we test the effect of Wal-Mart Supercenter and for non-grocery items we test the effect of Wal-Mart Discount Store. Following Basker (2005b) we consider Coke as non-grocery item. Sample period is 1990Q1-2014Q4.
***,**,* indicate significant at 1,5 &10 percent level respectively

2.5.2 Trend in Price Dispersion

We start our empirical analysis by plotting the time series trend of our bench-mark measure of price dispersion, MSE[38]. Figure-2.1 presents the time series of MSE averaged over all the city pairs on a quarter by quarter basis over the period of 1990 to 2014 for grocery and non-grocery items. i.e.

$$MSE_{\overline{ij},\ \ t} = \sum_{ij \in C} MSE_{ij,\ \ t} / C_T$$

where C is the set of city pairs ij=1,…..,C_T (in quarter t). The figure shows that the dispersion in grocery items on average is more than that of non-grocery items. Price dispersion of grocery items increases until 2005 and then steadily falls. On the other hand, for non-grocery items if we exclude shirt (a clear outlier[39]), the price dispersion remains more or less same, and below the price dispersion of grocery items for the entire period. Figure 2.2 and 2.3 show differences in price dispersion between low and high income cities, in non-grocery and grocery items respectively. In general price dispersion is lower in low income cities than in high income cities.

[38] Time trend using the other two measures are same as that of MSE.
[39] The dispersion in shirt price has increased sharply and steadily since 2001.

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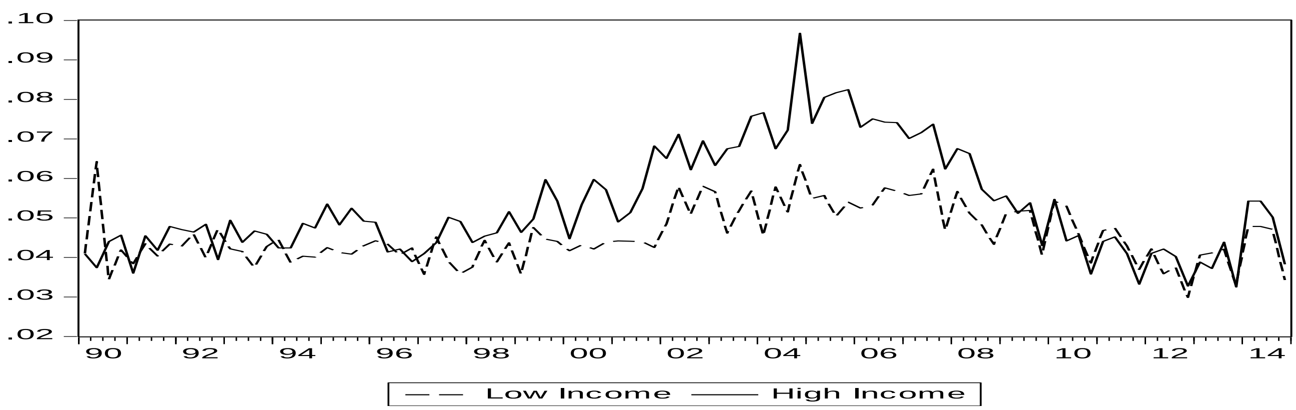
The low-income group consists of the bottom 30 low-income cities, whereas the high-income group consists of top 30 high-income cities.

Note: The quarterly time series of MSE is averaged over all the city pairs. Since there is a sharp increase in the price dispersion of shirt since 2001, we report MSE here both including and excluding shirt.

Figure 2.1: MSE of the dispersion of the commodities between cities.



Note: The quarterly time series of MSE is averaged over all the city pairs. The low-income group consists of the bottom 30 low-income cities, whereas the high-income group consists of top 30 high-income cities.

Figure 2.2: MSE for High and Low income cities (grocery items)

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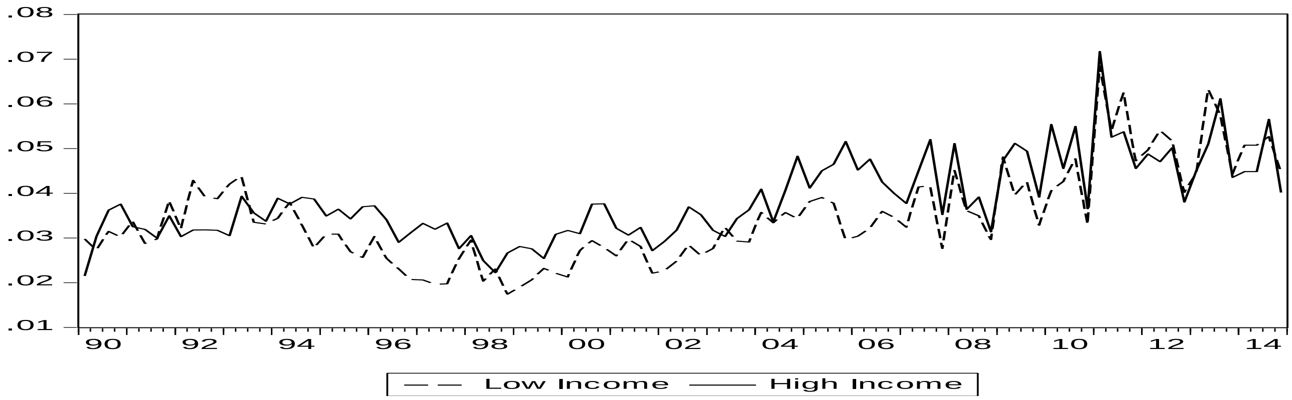

Note: The quarterly time series of MSE is averaged over all the city pairs. The low-income group consists of the bottom 30 low-income cities, whereas the high-income group consists of top 30 high-income cities.

Figure 2.3: MSE for High and Low income cities (Non-grocery Items)

2.5.3 Regression Analysis

We now turn to regression analysis to examine the effects of Wal-Mart on price convergence among US cities. We specify our benchmark empirical regression following equation (2). The most important arbitrage cost is transportation cost and empirically the distance between two cities provides an appealing proxy for such transportation cost. To account for local costs that may show up in retail prices we consider local rent and wage in the regression analysis. We do not include sales tax in our empirical regression as sales tax are applied only when the product is purchased. ACCRA data collectors collect data from shelves that means before sales-tax is added to the price. We include city fixed effects to capture the city specific characteristics that are not explicitly considered in the model. We also consider quarter fixed effects to capture the factors including changes in product definitions that may vary over time but common across all cities. Our variable of interest is Wal-Mart (discount) store for non-grocery items or Wal-Mart Supercenter for grocery items. Our benchmark regression is,

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$Y_{ij,t} = \alpha_0 + \alpha_1 \ln(Distance)_{ij} + \alpha_2 \left|\ln(R_{i,t}/R_{j,t})\right| + \alpha_3 \left|\ln(W_{i,t}/W_{j,t})\right| + \alpha_5(WM_{ij,t})$

$+\sum_i \beta_i\ City_i + \sum_j \beta_j\ City_j + \sum_{t=1990,q1}^{2014,q4} \lambda_t\ quarter_t + \mathcal{E}_{ij,t}$

Where $Y_{ij,t} = MSE_{ij,t}$ is the measure of price dispersion between cities i and j at period t, $Distance_{ij}$ is the driving distance between city i and j, $R_{i,t}$ and $R_{j,t}$ are rent in city i and j respectively in period t. $W_{i,t}$ and $W_{j,t}$ are wage in city i and j respectively in period t. $WM_{ij,t}$ is a dummy variable that takes 1 if both i and j have WM at period t, otherwise 0. City and quarter are variables representing city and quarter fixed effects.

Following Bergin and Glick (2007) and Basker (2005b) we use OLS method to estimate the model. Standard errors are clustered at the city pair level to address potential problems of heteroscedasticity and autocorrelation in the error terms.

Table 2 and 3 present the regression results for grocery and non-grocery items respectively. Column 2 shows the results from our benchmark regression model for the full sample. To see how sensitive our results are to sample-period, column 3 and 4 report the results from first and second half of the sample period respectively. Further, to see how sensitive our results are to city samples, column 5, 6, and 7 report the results from (i) when both the cities in the pair are from high income group, (ii) both the cities in the pair are from low income group (iii) one city in the pair is from high income and one city from low income group.

We expect distance, and the differences in wage and rent to be positively associated with price dispersion. On the other hand, we expect presence of Wal-Mart in both the cities to reduce the price dispersions, thus expect a negative sign. From table 2 and 3 it is evident that, distance is a significant predictor of price dispersion. For grocery items, Wal-Mart significantly help price convergence for all the specifications except in low income group. Specifically, average price dispersion is 0.21% to 0.45% lower if both the cities have Wal-Mart than if none or only one has

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Wal-Mart. For non-grocery items, Wal-Mart reduces price dispersion by .05% to .42%. However, they are statistically significant only for the high income group and for the second half of the sample period. In general, Wal-Mart's effect on price convergence is more prominent in the high income group than in the low income group. Differences in wages and rents are also positively related to price dispersion, and in most of the cases they are statistically significant for both grocery and non-grocery items. Since local wage and rent are likely to show up in the retail prices, differences in them between two cities are likely to contribute to the price differences between the two cities.

Table 2.3. Effects of the Presence of Wal-Mart on Price Dispersion (All grocery items together)

Sample	Full Sample	1990-2002	2002-2014	Both High Income	Both Low Income	One High Income-One Low Income
Distance	.0093***	.0089***	.0094***	.0114***	.0073***	.0069***
WM	-.0040***	-.0021***	-.0047***	-.0065***	.0005	-.0032***
Wage	.0061***	.0056***	.0204***	.0134***	.0027	.0017**
Rent	.0338***	.0169***	.0503***	.0411***	.0240***	.0283***
City Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.51	.56	.54	.48	.34	.42
Observations	467365	228531	238834	40548	39226	35970

Note: Dependent variable is MSE. Standard errors are clustered at the city pair level. While the 2nd column shows results for the whole sample-period, 3rd and 4th columns show results for the first and second half of the sample period respectively. 5th column shows the result when both the cities in the pair belong to high income group (top 30 cities out of 101 cities), while column 6 shows results when both the cities in the pair belong to low income group(lowest 30 cities out of 101 cities). Finally, last column shows the results when one city in the pair is from high income group and the other city in the pair from low income group. WM stands Wal-Mart dummy where it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

***,**,* indicate significant at 1,5 &10 percent level respectively.

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Table 2.4: Effects of the Presence of Wal-Mart on Price Dispersion (Non-Grocery Items)

Sample	Full Sample	1990-2002	2002-2014	Both High Income	Both Low Income	One High Income-One Low Income
Distance	.0033***	.0043***	.0023***	.0027***	.0028***	.0037***
WM	-.0005	-.0003	-.0042***	-.0021***	.0014	.0017
Wage	.0050***	.0030***	.0064***	.0111***	.0002	.0110***
Rent	.0115***	.0028***	.0201***	.0152***	.0171***	.0235***
City Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.21	.19	.22	.21	.22	.20
Observations	467365	467365	40548	40548	39226	35970

Note: Dependent variable is MSE. Standard errors are clustered at the city pair level. While the 2nd column shows results for the whole sample-period, 3rd and 4th columns show results for the first and second half of the sample period respectively. 5th column shows the result when both the cities in the pair belong to high income group(top 30 cities out of 101 cities), while column 6 shows results when both the cities in the pair belong to low income group(lowest 30 cities out of 101 cities). Finally, last column shows the results when one city in the pair is from high income group and the other city in the pair from low income group.

***,**,* indicate significant at 1,5 &10 percent level respectively.

Further, to see how Wal-Mart affects price dispersion of individual commodities, we analyze the effect of Wal-Mart on the products individually. Specifically, we estimate the following equation, for each product.

$$\left|\ln(P_{i,t}^k/P_{j,t}^k)\right| = \alpha_0 + \alpha_1 \ln(Distance)_{ij} + \alpha_2 \left|\ln(R_{i,t}/R_{j,t})\right| + \alpha_3 \left|\ln(W_{i,t}/W_{j,t})\right| + \alpha_5(WM_{ij,t}) + \sum_i \beta_i\, City_i + \sum_j \beta_j\, City_j + \sum_{t=1990,q1}^{2014,q4} \lambda_t\, quarter_t + \mathcal{E}_{ij,t}$$

The results are reported in table 4. The results show that out of 24 products, for 16 products the signs of the coefficients of WM are negative which means Wal-Mart helps price convergence of those commodities. Of them, 14 (11 grocery and 3 non-grocery) are even statistically significant. Among the other variables distance is significantly and positively related to the price dispersion of all of the goods. Differences in rent and wage are also positively and significantly related to the price dispersion of most of the goods.

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The grocery items for which Wal-Mart helps price convergence significantly are banana, bread, coffee, corn, cornflakes, eggs, lettuce, milk, potato, sugar and tuna. The highest convergence effect of Wal-Mart being on bread (1.93%). The three non-grocery items for which Wal-Mart helps price convergence significantly are shampoo, toothpaste and facial tissue with the highest convergence effect on Shampoo (1.47%).

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Table 2.5: Effects of the Presence of Wal-Mart on Price Dispersion (Individual Commodities).

	Distance	WM	Wage	Rent	City fixed effect	Quarter fixed Effect	R^2	Observa-tions
Banana	.0136***	-.0092***	.0391***	.0566***	Yes	Yes	0.2	463355
Beef	.0123***	-0.0016	.0362***	.0459***	Yes	Yes	0.13	463355
Bread	.0121***	-.0193***	-.0174***	.0173***	Yes	Yes	0.17	463355
Cheese	.0332***	0.0002	-0.005	.1021***	Yes	Yes	0.28	463355
Chicken	.0191***	-0.0012	.0347***	.0610***	Yes	Yes	0.14	463355
Coffee	.0309***	-.0026*	-.0147***	.1080***	Yes	Yes	0.24	463355
Corn	.0075***	-.0150***	0.0041	.1004***	Yes	Yes	0.18	463355
Cornflakes	.0184***	-.0095***	.0199***	.0609***	Yes	Yes	0.17	463355
Eggs	.0207***	-.0166***	.0147***	.0667***	Yes	Yes	0.14	463355
Lettuce	.0283***	-.0062***	-.0070**	0.0036	Yes	Yes	0.13	463355
Margarine	.0219***	0.0015	-.0198***	.0696***	Yes	Yes	0.21	463355
Milk	.0188***	-.0069***	.0376***	-0.0021	Yes	Yes	0.12	463355
Peaches	.0124***	.0088***	-.0245***	.0749***	Yes	Yes	0.25	463355
Potato	.0575***	-.0173***	-0.0066	-.0445***	Yes	Yes	0.14	463355
Steak	.0182***	0.0008	.0190***	.0064***	Yes	Yes	0.12	463355
Sugar	.0075***	-.0059***	.0197***	.0314***	Yes	Yes	0.13	463355
Sweet peas	.0195***	.0084***	.0215***	.0766***	Yes	Yes	0.15	463355
Tuna	.0190***	-.0064***	.0144***	.0834***	Yes	Yes	0.13	463355
Coke	.0078***	.0173***	.0740***	.0066**	Yes	Yes	0.14	463355
Detergent	.0132***	0.0017	-0.0014	.0337***	Yes	Yes	0.13	463355
Facial Tissues	.0120***	-.0033**	-.0088***	.0280***	Yes	Yes	0.14	463355
Shirt	.0025***	0.0008	-0.0063	.0154***	Yes	Yes	0.21	463355
Shampoo	.0093***	-.0147***	.0242***	.0435***	Yes	Yes	0.17	463355
Tooth paste	.0071***	-.0107***	-.0221***	.0207***	Yes	Yes	0.14	463355

Note: Dependent variables are the ln of relative prices, $\ln(P_{i,t}^{k}/P_{j,t}^{k})$ WM stands Wal-Mart dummy where it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

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2.6 ROBUSTNESS CHECK

To check robustness of our benchmark results (1) we use two other measures of price dispersion namely DMSE and MAD. (2) we divide the full sample into three sub-samples: the first sub-sample includes city pairs with either both of the cities have Wal-Mart or none of them has Wal-Mart, the second sub-sample includes city pairs with either both of the cities have Wal-Mart or only one of them has Wal-Mart, the third sub-sample includes city pairs with either one of the cities has Wal-Mart or none of them has Wal-Mart. Table 5 shows that the findings using DMSE and MAD as regressand are in line with the findings of our benchmark model.

Table 2.6: Regression Results (with MAD and DMSE as Dependent Variable)

	Grocery		Non-Grocery	
Dependent Variable	DMSE	MAD	DMSE	MAD
Distance	.0093***	.0206***	.0034***	.0086***
WM	-.0043***	-.0050***	-.0006	-.0008
Wage	.0064***	.0092***	.0052***	.0099***
Rent	.0297***	.0510***	.0117***	.0246***
Quarter fixed effect	Yes	Yes	Yes	Yes
City fixed Effect	Yes	Yes	Yes	Yes
Observations	463355	463355	463355	463355
R^2	.40	.44	0.22	0.22

Note: WM stands Wal-Mart dummy where it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

Table 6 and 7 show results from our second robustness check for grocery and non-grocery items respectively. In first specification (second column) we assume WM is 1 if both of the cities in the pair have Wal-Mart, and 0 if none of the cities in the pair has Wal-Mart. In line with our hypothesis we expect that the coefficient of WM to be negative. In the second specification (3rd column) we assume WM is 1 if both of the cities have Wal-Mart, and 0 if one of the 2 cities has Wal-Mart. Again, in line with our hypothesis we expect the coefficient to be negative. In the third specification (fourth column) we assume WM is 1 if one of the two cities in the pair has Wal-Mart, and 0 if none of them has Wal-Mart. Since Wal-Mart influences the city-prices we

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expect price dispersion to be more if one of the cities of the pair has Wal-Mart than no cities in the pair has Wal-Mart. Accordingly we expect the coefficient of WM to be positive. Table 6 and 7 show that signs of the coefficients of Wal-Mart are according to our hypothesis, and most of them are statistically significant.

Table 2.7: Regression Results for Sub-Sample (Grocery items)

	Both vs None	Both vs One	One vs none
Distance	.0106***	.0093***	.0096***
WM	-.0006	-.0018***	.0021***
wage	.0046***	.0085***	.0078***
rent	.0524***	.0367***	.0231***
City fixed effect	Yes	Yes	Yes
Period fixed effect	Yes	Yes	Yes
Observations	339660	344892	242158
R^2	.27	.43	.42

Note: Dependent variable is MSE. ‘Both’ implies both the cities of the pair have Wal-Mart, ‘none’ implies none of the cities in the pair has Wal-Mart, ‘One’ implies one of the cities in the pair has Wal-Mart.

Table 2.8: Regression Results for Sub-Samples (Non-Grocery items)

	Both vs None	Both vs One	One vs none
Distance	.0034***	.0033***	.0036***
WM	-.0050***	-.0005	.0026***
wage	.0076***	.0043***	.0012
rent	.0178***	.0102***	.0083***
City fixed effect	Yes	Yes	Yes
Period fixed effect	Yes	Yes	Yes
Observations	386391	453314	94460
R^2	.33	.21	.24

Note: Dependent variable is MSE. ‘Both’ implies both the cities of the pair have Wal-Mart, ‘none’ implies none of the cities in the pair has Wal-Mart, ‘One’ implies one of the cities in the pair has Wal-Mart.

2.7. REGIONAL ANALYSIS

To see further if the impact of Wal-Mart in price convergence differs between the regions, we divide our full sample based on BEA regional classification. The regions are New England, Mideast, and Great Lake regions (Region 1, Total cities 23) [40] , Plains Region (Region

[40] Since New England and Mideast regions together have only 5 cities in the sample, we merge them with great lake region.

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2:Total cities 12), Southeast Region (Region 3, Total cities 29), Southwest Region (Region 4, Total cities 20), Rocky Mountain Region (Region 5, Total cities 10), Far West Region (Region 6, Total cities 8). Table 8 and 9 show the results from regional analysis for grocery and non-grocery items respectively. For grocery items Wal-Mart helps price convergence significantly in three regions namely region 1, Plains and Rocky Mountain. For non-grocery items Wal-Mart helps price convergence significantly only in Far West. However, with a sharp contrast to the results from full-sample, in region 3, presence of Wal-Mart is positively and significantly associated with price dispersion of both grocery and non-grocery items.

Table 2.9: Regression results for regional city pairs (For grocery items).

Dependent Variable	Region 1	Plains	Southeast	Southwest	Rocky Mountain	Far West
Distance	.0096***	.0039***	.0065***	.0146***	.0103***	.0101***
WM	-.0095***	-.0033*	.0033***	.0011	-.0084*	-.0014
Wage	-.0039	-.0002	-.0014	.0084**	.0146	.0247
Rent	.0513***	-.0067	-.0018	.0346***	.0201***	.0182**
Quarter fixed effect	yes	yes	yes	yes	yes	yes
City fixed Effect	yes	yes	yes	yes	yes	yes
Observations	22104	6165	38120	17404	4248	1919
R^2	.43	.36	.29		.45	.44

Note: Dependent Variable is MSE. A city pair in a region includes only the cities belong to that region. The regions are based on BEA regional classification. Region 1 includes New England, Mideast, and Great Lake regions. WM stands Wal-Mart dummy where it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

Table 2.10 : Regression results Regional city pairs (For non-grocery items)

Dependent Variable	Region 1	Plains	Southeast	Southwest	Rocky Mountain	Far West
Distance	.0040***	.0067***	.0031***	.0046***	.0035**	.0027**
WM	.0002	-.0005	.0031**	.0006	.0002	-.0029*
Wage	.0047	-.0060	-.0018	.0118***	-.0078	-.0326
Rent	.0357***	.0169	-.0034	.0087**	-.0020	.0222***
Quarter fixed effect	yes	yes	yes	yes	yes	yes
City fixed Effect	yes	yes	yes	yes	yes	yes
Observations	22104	6165	38120	17404	4248	3349
R^2	.27	.26	.23	.29	.28	.32

Note: Dependent variable is MSE. A city pair in a region includes only the cities belong to that region. The regions are based on BEA regional classification. Region 1 includes New England, Mideast, and Great Lake regions. WM stands Wal-Mart dummy where it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

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2.8 WAL-MART'S EFFECTS ON PRICE CONVERGENCE OF SERVICES

We also examine the effects of the presence of Wal-Mart on price convergence of services. From the list of ACCRA data, our selection of services is limited to those items consistently available in the ACCRA survey during the period of our study. The services we consider are beauty salon, hair-cut, tire-balance, wash repair, bowling, dry clean, hospital bed and doctor visit. Of these, Wal-Mart provides hair-cut, beauty salon and tire balance services. So we expect Wal-Mart's role in the price convergence of these services. We report the regression results in table 10. Though Wal-Mart helps price convergence of hair-cut and beauty salon significantly, its presence is significantly associated with the price divergence of the tire balance service. The other services are not produced by Wal-Mart. As expected, Wal-Mart does not have any significant effect on the price convergence of bowling, dry clean and hospital bed. Such insignificant effect of Wal-Mart on the services that Wal-Mart does not produce re-assures that our previous results are not driven by any unobservable factors like demand or cost differences. However, we also find that Wal-Mart has significant converging effect on doctor visit and washing machine repair services that it does not produce. This could be interpreted as Wal-Mart's indirect effect. Basker and Noel (2009) use an aggregate measure of six services namely wash repair, movie ticket[41], bowling, hair cut, beauty salon, dry cleaning. They show that Wal-Mart does not have significant price effect on that aggregate measure of the services. Since they do not report the results of individual services, we cannot compare their results with ours. An analysis of the channels through which Wal-Mart may affect some of the services indirectly, even though it does not produce those, could be interesting but clearly out of the scope of this paper.

[41] We can not include movie ticket as the series is discontinued.

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Table 2.11: Effects of the Presence of Wal-Mart on Service Price Dispersion

	Distance	WM	Wage	Rent	City fixed effect	Quarter fixed Effect	R^2	Observa-tions
Beauty Salon	.0084***	-.0077***	.0443***	.0794***	Yes	Yes	.19	463355
Bowling	.0155***	.0009	-.0200***	.0322***	Yes	Yes	.20	463355
Doctor visit	.0056***	-.0068***	.0265***	.0161***	Yes	Yes	.23	463355
Dry Clean	.0123***	-.0000	-.0062	.0348***	Yes	Yes	.22	463355
Hair cut	-.0009	-.0080**	-.0196***	.0723***	Yes	Yes	.22	463355
Hospital bed	.0354***	.0010	-.0117	.2838***	Yes	Yes	.39	463355
Tire Balance	.0018	.0053**	.0165***	.0239***	Yes	Yes	.21	463355
Wash Rep	.0071***	-.0054*	-.0355***	-.0115*	Yes	Yes	.23	463355

Note: Dependent variables are the ln of relative prices, $\ln\left(\frac{P_{i,t}^k}{P_{j,t}^k}\right)$. WM stands Wal-Mart dummy, it assumes 1 when both of the city pairs have Wal-Mart, 0, otherwise.

2.9 DISCUSSIONS OF THE RESULTS

Our analyses show that though there is enough evidence in favor of our hypothesis that Wal-Mart helps price convergence, there are also asymmetries in the impact of Wal-Mart on price convergence. For example, whereas Wal-Mart's presence is positively and significantly associated with price convergence of almost 80% of the grocery items, its presence helps price convergence significantly only for 3 out of 6 non-grocery items. Though the number of non-grocery items in our analysis is too few to deduce any correlation between Wal-Marts' presence and price convergence of non-grocery commodities, non-grocery items seem less likely to be affected by Wal-Mart. It in turn implies that Wal-Mart has strong bargaining capacity with most of the grocery producers, but not with many of the non-grocery producers. Wal-Mart's significant effect on the prices of food and grocery items is also documented by Hausman et al. (2007), Volpe and Lavoie (2007), and Basker and Noel (2009). Wal-Mart's business strategy

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and relative bargaining capacity with the producers of individual commodities should give more insights into its influence over the prices.

Nevertheless, Wal-Mart's significant role in grocery-price convergence has several implications. First, it implies that Wal-Mart helps efficient transportation of the grocery items from the places they are produced to other places. Second, by helping price convergence of grocery items Wal-Mart is playing a catalyst role in convergence of the income of farmers and small producers across the regions. Therefore, Wal-Mart helps market integration, and increase efficiency and welfare through a convergence of prices in grocery markets.

In addition, we find Wal-Mart's more significant role in price convergence between the cities in the group of top 30 high income cities than in the group of bottom 30 low income cities. In the low income cities prices are already low, and Wal-Mart's effect on price is not much. On the other hand, in the high income cities where the prices are high, Wal-Mart has more scope to affect the prices. Since Wal-Mart is expected to have more prominent effect on the price of high income cities than on the prices of low income cities, Wal-Mart's more prominent role in price convergence between two high income cities than between two low income cities is not surprising[42].

There are significant variations in the time path of the convergence of individual commodities[43]. For example, the price dispersion of shirt across cities has sharply and consistently increased since 2001, whereas price dispersion in Coca-Cola steadily decreased throughout our sample period (see appendix 1). While inquiring into the case of shirt price, we notice that there is a sharp increase in import of readymade garments since 2001. Therefore,

[42] This finding matches with a recent paper (), which finds price convergence is faster for high priced goods than low priced goods.
[43] We have not reported the time path of price dispersion of individual commodities here but available upon request.

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there might be some links between import and price convergence. Our analysis (not reported here) shows that in West-Coast, price dispersion in shirt is less than that in other regions. However, to establish a concrete relation between import and price dispersion, more rigorous analysis is warranted, which is out of the scope of this paper.

Our regional analysis also gets us some interesting results. First there are significant differences in the effect of Wal-Mart on price convergence across regions. This is not surprising. Many studies that test Wal-Mart's effect on a region, get significantly different results from the studies conducted on national data[44]. Second, albeit surprisingly, Wal-Mart's effect on price convergence is less pronounced within a region than that nationally. For grocery items whereas in region 1, 2 and 5 Wal-Mart helps price convergence significantly, in region 3, its presence is significantly associated with price dispersion. For non-grocery items, Wal-Mart helps price convergence significantly only in one region. Wal-Mart's more prominent role in national data and less prominent role in regional data imply that Wal-Mart is helping price convergence between distant cities more than between nearby cities. Or, in other words, Wal-Mart is helping the regions to come closer in terms of price but not necessarily the cities within a region. From a policy perspective, our regional analysis warns against the generalization of the findings of the studies on national data. A region's demography, population density, economy among others may impact Wal-Mart's impact on that region.

[44] For example, Volpe III and Lavoie (2007), Hicks (2001), Paruchuri et al. (2009).

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2.10 CONCLUSION

Building on the literature of the effects of various factors on deviations from the law of one price, we formulate the hypothesis that Wal-Mart plays a vital role in price convergence among US cities. We argue that, prices are significantly closer in two cities if they have Wal-Mart than if none or only one of them has Wal-Mart. To test our hypothesis we combine two data sets: one contains locations and opening/conversion dates of Wal-Mart discount store and supercenters; and the other includes city level retail prices from American Chamber of Commerce Research Association (ACCRA). Following previous literature we use mean square error (MSE) as our benchmark measure of price dispersion. We find that prices of grocery items are significantly closer in two cities if they have Wal-Mart than if none or only one of them has Wal-Mart. Though Wal-Mart helps price convergence of non-grocery items the results are not statistically significant for many specifications. When the products are analyzed individually, we find that out of 24 products, for 16 products Wal-Mart helps price convergence, 14 of them are even statistically significantly. We also find that Wal-Mart effect is more prominent in high-income cities than in low income cities. However, when we analyze region-wise, Wal-Mart's effect is not so prominent as it is on national data.

From an academic perspective the contribution and novelty of our analysis is that we combine two highly active but distant research areas, namely the effect of Wal-Mart on retail price, and market integration in the US cities. In doing so we propose a new avenue to consider when analyzing the potential drivers of price convergence. From a policy perspective the contribution of this paper is that it adds to the information required by the policy makers on the socio-economic impact of Wal-Mart.

However, there are still some open questions and many things are yet to be done. Especially, issues such as why for some of the commodities Wal-Mart does not help price

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convergence, or why within a region Wal-Mart's effect on price convergence is less pronounced than that nationally, merit separate analyses. Moreover, different time path of price convergence of the individual commodities deserve further insights. We leave all these issues for future research.

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CHAPTER 3

WAL-MART'S EFFECT ON LOCAL ECONOMIC ACTIVITIES AND REVENUE

3.1 INTRODUCTION

Few issues receive as much debate in local communities as the expected opening of a Wal-Mart. Over the past 25 years communities across the United States (and increasingly worldwide) have seen both benefits and costs associated with the entrance of the retailing giant (Hicks 2007).

On one side, Wal-Mart proponents typically argue that the new store will increase employment, attract additional commercial development, foster lower prices on consumer goods, and generate higher levels of tax revenue by increasing the tax base (Vandegrift and Loyer 2015). In contrast, opponents contend that Wal-Mart drives out smaller, locally owned businesses, leaving vacant tracts of property and reducing property values. Worse yet, the bankruptcies cause a decrease in wages and an increase in unemployment (Vandegrift and Loyer 2015).

Because ultimate authority for new development typically rests with the local government and planning board, the economic and fiscal impact of the new Wal-Mart on the economic activities and revenue is often the focus of the debate (Vandegrift and Loyer 2015). Presence of Wal-Mart can both increase and decrease economic activities such as total retail sales. On one hand, the competitors of Wal-Mart may leave the locality; on the other hand the stores that produce complementary products may increase. Jia (2005) argues that Wal-Mart's expansion alone explains 50–70 percent of the net exit of small discount retailers between 1988 and 1997. Basker (2005a) finds that, in total, approximately four small competitors close within five years of Wal-Mart's entry. On the other hand, in a study on Iowa, Stone (1997) finds that

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total sales of local restaurants and eating and drinking establishments are increased an average of five per cent ten years after a Wal-Mart opening.

Wal-Mart may induce consumers to spend more. If this is true then increase in sales because of a new Wal-Mart store may overshoot the decrease in sales by the replaced mom-and-dad stores. This phenomenon along with the possibility of new opening of complementary stores like restaurants is likely to increase total retail sales if Wal-Mart comes to the locality.

Wal-Mart may have effect on local tax rates as well. In Florida in addition to state sales tax rate, a discretionary sales surtax can be imposed by counties. Wal-Mart may influence local authority for tax abatement which is then applicable for other stores as well. The competition for the Wal-Mart in their area may encourage local governments to offer tax rebatement. Mattera & Purinton (2004) compiled a very long list of examples of Wal-Mart employing local tax incentives (tax increment financing, infrastructure grants, property tax abatement, etc.) to support growth (Hicks 2007).

Total sales-tax revenue depends on total sales and sales tax rate. For a given sales-tax rate, if total sales increase, revenue from sales tax also increases. Likewise, for a given total sales, revenue will be more if tax rate is higher. Wal-Mart can affect local sales-tax revenue by affecting total sales and/or sales tax rate.

We examine the effect of Wal-Mart on total retail sales, total taxable retail sales, total sales tax and sales tax rate in the counties of Florida. Because of its open record policy Florida is famous for granting access to a rich lineup of publicly available database. More importantly recent population and economic growth of Florida are much higher than the other states. Therefore it would be interesting to consider Florida as a case study in this regard.

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The remaining of the paper proceeds as follows. Section 2 reviews the literature, section 3 describes data, section 4 presents empirical identification and estimation strategy, section 5 provides estimated results, and finally section 6 concludes.

3.2 LITERATURE REVIEW

A number of studies examine the effects of Wal-Mart on various economic and social indicators that range from price to wage, obesity to crime, inequality to competition. Basker (2005b) tests the price effect of Wal-Mart entry on ten non-grocery items and finds that Wal-Mart reduces the prices of almost all the items with detergent, shampoo, and tooth paste even statistically significantly. Hausman et al. (2007) show that Wal-Mart supercenters have big impact on retail price of food, as they offer groceries at 15%–25% lower than traditional supermarkets. Basker and Noel (2009) estimate a short-run 1–2 percent price reduction by competing grocery stores due to Wal-Mart's entry, whereas Glandon and Jaremskif (2014) show that individual stores offer more discounts as the distance to Wal-Mart falls[45]. In general, Wal-Mart's effect on existing local retailers is negative, although some complementary businesses may benefit from Wal-Mart's presence (Irwin and Clark 2006).

Several studies have examined Wal-Mart's effect on the tax base and tax revenues (Vandegrift and Loyer, 2015; Muller and Humstone, 1996; Hicks, 2007; Johnson et al., 2009). Vandegrift and Loyer (2015) find that a new Wal-Mart has no significant effect on the growth in the tax base in either the host or the adjacent municipality in New Jersey. Muller and Humstone (1996) tests Wal-Mart's effect on three communities and nine counties in Iowa. They show that Wal-Mart initially adds $2 million to the local tax base though many businesses began to close

[45] Other studies on the effect of Wal-Mart include but not limited to Basker (2005a) and Neumark et al. (2005) on labor market, Pope and Pope (2015) on land price, Wolfe and Pyrooz (2014) on crime.

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following Wal-Mart's entrance. Hicks (2007) analyzes Wal-Mart's effect on county level commercial and industry property tax revenue using a panel of Ohio's 88 counties for the years 1985-2003 and finds that a Wal-Mart increases county level property tax collections between $350000 and $1.3 million annually. Zhu et al. 2005 shows that the entry of a Wal-Mart store that does not sell groceries in Chicago increased revenue at an adjacent grocery store, but reduced revenue at a grocery store two miles away. Analogously, Stone (1997) finds that restaurant sales in Wal-Mart towns in Iowa were 5 percent higher than the state average, while restaurant sales in non-Wal-Mart towns were 9 percent lower than the state average even 10 years after the Wal-Mart opened. Artz and McConnon (2001) also find evidence that the entry of a Wal-Mart altered the retail market structure by increasing sales in "host towns" in Maine and decreasing sales in surrounding communities. Thus, they claim, shoppers from non-Wal-Mart towns shopped in Wal-Mart towns and, while there, patronized other businesses as well.

3.3 DATA

To examine Wal-Mart's effect on local sales, tax revenue and tax rate we collect data on Wal-Mart's location and opening dates from Holmes (2008) for the period 1990-2006. Annual data on county level total retail sales, taxable sales, and sales tax are collected from Florida department of Revenue website. Population and personal income data are obtained from US census bureau. Sales, taxable sales, sales taxes and income are in 2005 dollar. Distance data are great circular distances calculated using longitudes and latitudes of the locations. Following previous works we construct three dummies for distance: dummy 1 for less than 100 miles, dummy 2 for less than 200 miles but greater than 100 miles, and dummy 3 for distance greater than 200 miles. We use annual data and the sample period covers 1990-2006. Selection of sample period is based on the availability of data.

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3.4 EMPIRICAL APPROACH AND IDENTIFICATION[46]

We estimate models for changes in retail sales, taxable sales, sales taxes and sales tax rates. We generally capture increased exposure to Wal-Mart stores via a measure of store openings in a county-year cell—i.e., the change in the number of stores. We define changes in retail sales, taxable sales and sales taxes and number of stores on a per person basis, to eliminate the undue influence of extraordinarily large counties. As long as we divide all of these changes by the number of persons in the county, the estimated coefficient on the Wal-Mart variable still measures the effect of a Wal-Mart store opening on the change in the level of retail sales, taxable sales and sales taxes. To control for overall income growth that may affect the level of demand for retail, we include changes in personal income per person as a control variable. As we will use first difference of the variables, the county level characteristics that do not change over time will automatically be taken care of. However we will be using year fixed effects in our model.

We denote the county-level measures of retail sales, taxable sales, sales tax (all in per person) and sales tax rate as *Y*, the number of Wal-Mart stores (per person) as *WM*[47], total personal income per person as *PI*, and year fixed effects (in year *s*) as *YRs* . Indexing by county *j* (*j* = 1, . . . , *J*) and year *t* (*t* = 1, . . . , *T*), and defining α, β, γ , and δs as scalar parameters, our baseline model for the change in the dependent variable for each observation *jt* is:

$$\Delta Y_{jt} = \alpha + \beta \Delta WM_{jt} + \gamma \Delta PI_{jt} + \sum_{s=1}^{T} \delta_s YR_s + \varepsilon_{jt} \qquad (1)$$

Fixed county differences in the levels of the dependent variables drop out of the first-differenced model.

[46] This section is heavily drawn from Neumark et al. (2008).
[47] In the tax rate equation we only consider change in Wal-Mart not Wal-Mart per person.

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3.4.1 ENDOGENEITY OF WAL-MART LOCATION DECISION AND IDENTIFICATION

Consistent estimation of Eqn. (1) requires that ε_{jt} is uncorrelated with the right-hand-side variables. If Wal-Mart location decisions are based in part on contemporaneous and future changes in retail sales and/or tax rate, then this condition could be violated. This endogeneity is natural, since Wal-Mart would be expected to make location decisions (including the location and timing of store openings) based on current conditions and future prospects, which might be related to retail sales and tax rate. As but one example, Wal-Mart may open stores where real estate development and zoning have recently become favorable to retail growth.

Thus, to ensure that our analysis captures only the changes in the dependent variables that occur because Wal-Mart has opened a store, we need additional controls. One possibility is to follow Basker (2005a, 2005b). Basker attempts to isolate the effect of Wal-Mart on wages by using an instrument that proxies for a store's initial planning date (i.e., company assigned store number). By contrast, Dube et al. (2005) and Neumark et al. (2008) exploit geographic regularities in Wal-Mart's expansion from a single store in Benton County, Arkansas to determine the impact of Wal-Mart on county-level retail employment and earnings. To preserve density, Wal-Mart opened new stores near existing stores. Given this, Dube et al. (2005) and Neumark et al. (2008) instrument for Wal-Mart openings using the interaction of time and distance from Benton County, Arkansas.

Unfortunately, the identification strategy employed by Dube et al. (2005) and Neumark et al. (2008) is not appropriate for our data because this diffusion from the starting point in Benton County ended in the late-1990s. After the late-1990s, Wal-Mart's growth was evenly distributed across the distance gradient (Dube et al., 2005). As a result, we cannot employ a time/distance

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interaction to Benton County to examine the impact of new Wal-Mart stores in Florida during the period 1990–2006.

Instead we use the shortest of the great circular distances from Monatee and Volusia Counties to predict where and when Wal-Mart stores will open. These counties are two of the first counties in Florida where Wal-Mart opened stores. Other stores were opened mostly centering these two stores. Apart from distance and year dummy in Wal-Mart opening equation we also use an interaction term between distance and year dummy to capture the fact that the probability of openings is higher early in the sample period in locations near these two counties, but higher later in the sample period further away from these two Counties.

$$\Delta WM_{jt} = \sum_{i=1}^{J} \lambda_i \, Dist_i + \sum_{s=1}^{T} \mu_s YR_s + \sum_{s=1}^{T} \sum_{i=1}^{J} \vartheta_{is}(DIST_i * YR_s) + \pi X_{ij} + \eta_{jt} \qquad (2)$$

Where Dist is the shortest of the great circular distances from the two counties. As already mentioned Dist is a dummy variable. The first dummy is for less than 100 miles, the second one is for less than 200 miles but greater than 100 miles, and the third dummy is for distance greater than 200 miles. YR_S is the year dummy, and Dist * YRs is the distance-time interaction. X_{ij} is the vector of other control variables that may affect decision of Wal-Mart opening. In particular X_{ij} includes lags of the growth and level of total retail sales per capita, sales-tax rate and per capita income. In IV estimation, in first stage we estimate eq^n 2, get the predicted ΔWM_{jt} and then in equation 1 we use the predicted value instead the original value of Wal-Mart.

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3.5 EMPIRICAL RESULTS

We start our empirical analysis with some descriptive statistics. Table 1 reports the mean value of all the 64 counties by year. Table 2 reports mean value of all the 17 years by county. The tables show that usually the counties with more Wal-Marts are associated with more sales and lower tax rate.

Table 3.1: Summary statistics by year

Year	Per Capita Sales (in 2005 $)	Per Capita Taxable Sales (in 2005 $)	Per Capita Sales Tax (in 2005 $)	Sales Tax Rate	Per Capita Personal Income (in 2005 $)	Population	WM
1990	20516.7	10354.7	640.302	6.219208	25277.29	194527	1.537313
1991	19868.5	9881.751	605.7022	6.165612	24878.35	199549.2	1.686567
1992	19608.27	9814.555	600.6757	6.158114	25399.84	203739.6	1.746269
1993	20098.21	10031.85	620.5093	6.215536	25677.04	207868.4	1.80597
1994	20603.92	10074.67	626.9314	6.309939	25960.56	212529	1.880597
1995	21689.05	10384.65	648.3001	6.328504	26731.26	216983.2	1.925373
1996	22314.98	10642.26	667.4264	6.364189	27285.46	221691.9	1.970149
1997	22794.28	10810.22	675.1305	6.343072	27915.13	226661.3	1.985075
1998	23203.23	11227.7	706.6782	6.389827	29092.48	231142.7	2.014925
1999	23803.76	11661.28	727.0424	6.342966	29549.45	235215.2	2.044776
2000	25371.91	12089.95	750.5258	6.31452	30363.32	239515.1	2.074627
2001	25655.62	12025.19	750.1924	6.345409	31034.53	244133.8	2.149254
2002	25048.14	11720.17	729.753	6.34758	30678.5	249095.1	2.208955
2003	25009.52	11452.01	712.3433	6.370768	31119.34	253792.3	2.283582
2004	25678.16	11941.05	727.3409	6.220668	32416.34	259930.1	2.402985
2005	27362.38	12674.16	787.2459	6.365924	33392.57	266299.1	2.537313
2006	30157.7	14016.76	890.0634	6.520757	34395.39	271149.1	2.626866

Note: Mean of all the 64 counties by year.

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Table 3.2: Summary statistics by counties.

County	Per Capita Sales (in 2005 $)	Per Capita Taxable Sales (in 2005 $)	Per Capita Sales Tax (in 2005 $)	Sales tax rate	Per Capita Personal Income (in 2005 $)	Population	WM
Alachua	24810.06	13699	830.8434	6.070381	29795.32	212045.6	2
Baker	23041.72	5219.391	335.5593	6.425025	23405.56	21724.76	1
Bay	28952.86	17037.56	1061.459	6.225182	30032.11	146470.9	3
Bradford	14959.18	7532.023	462.841	6.142366	22212.91	25554.18	1
Brevard	28126.47	12820.49	789.709	6.158682	32269.51	469512.9	6.176471
Broward	41249.5	17040.04	1037.436	6.088349	37733.32	1539902	8.058824
Calhoun	11931.22	5308.643	339.7213	6.409966	19649.8	12531.29	0
Charlotte	20539	12872.17	799.5356	6.209401	30193.37	137719.4	2.823529
Citrus	16367.3	9573.357	590.7886	6.169686	26250.67	114725	2
Clay	20271.43	10869.46	666.2429	6.127749	32232.75	136841.4	1.352941
Collier	33852.97	21118.93	1305.589	6.181918	51328.78	233320.3	1.941176
Columbia	26194.14	12488.97	765.9442	6.131225	23677.6	53624.35	1
DeSoto	15588.43	7415.115	488.2509	6.583136	21792.84	30062.76	1
Dixie	14300.06	4965.646	315.2918	6.311999	19318.81	13241.59	0
Duval	42397.31	17434.8	1057.957	6.066032	34148.5	761535.5	7.235294
Escambia	28545.79	14240.54	876.2435	6.150748	28840.63	286872.7	3.235294
Flagler	17462.47	8104.08	507.5837	6.263902	28872.18	49740.35	1
Franklin	17056.14	10093.65	644.1534	6.376446	24964.63	10184.94	0
Gadsden	20569.53	5673.888	356.7476	6.284893	23739.7	44170	1
Gilchrist	8886.923	3424.337	220.8339	6.45159	23565.62	13305	0
Glades	8482.526	2863.814	187.929	6.608102	20878.23	9910	0
Gulf	15248.37	7390.191	460.0593	6.240135	22980.62	13504.24	0
Hamilton	11954.36	8352.169	536.2131	6.496691	18190.21	12669	0
Hardee	15217.9	6822.049	420.5611	6.16238	21874.81	24921.65	1
Hendry	33428.05	9027.116	565.1555	6.262271	24924.02	33535.41	0.529412
Hernando	29374.69	8170.479	505.1644	6.184076	27485.82	128863.9	2.235294
Highlands	19260.52	10416.78	647.7438	6.215909	25706.6	84291.24	1
Hillsborough	45879.84	18722.86	1141.228	6.095372	33289.3	978365.1	8.647059
Holmes	8726.086	4008.168	280.2306	6.996663	21329.65	18040.59	0
Indian River	26165.27	14570.26	902.1735	6.189838	47057.27	109529.7	2
Jackson	18546.94	8674.365	550.3449	6.341083	23154.06	45465.65	1
Jefferson	9962.854	4094.874	368.0456	9.013235	26619.68	13119.24	0

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Table 3.2: Summary statistics by counties(Continued)

Lafayette	10290.38	3282.966	217.9814	6.651234	19234.4	6701.412	0
Lake	21197.3	11135.79	687.3712	6.170815	30286.76	204695.2	2.176471
Lee	29406.01	18307.73	1124.709	6.143237	34839.43	435230.6	3.882353
Leon	26012.94	14717.34	914.8046	6.213196	32169.06	231357.9	3
Levy	15354.57	7806.647	483.7425	6.199797	23116.89	32734.24	1
Liberty	11169.41	3459.349	256.3774	7.376898	21626.83	6820.353	0
Madison	10278.71	4684.041	316.7884	6.76257	20547.39	18159.47	0
Manatee	27927.74	13487.45	828.7354	6.145728	36166.47	257512.1	3.117647
Marion	29367.8	12984.95	795.517	6.126526	27081.73	250104.4	3.294118
Martin	32904.58	18535.54	1144.725	6.178807	51407.22	122777.2	1
Miami-Dade	42185.24	14875.12	898.5753	6.040978	31859.64	2183384	3.294118
Monroe	40420.38	28091.01	1748.616	6.221694	46034.19	79307.47	0
Nassau	27545.77	11259.45	700.7153	6.22093	35057.68	55378.65	1.176471
Okaloosa	28343.29	15599.58	974.2287	6.243464	34807.71	167256.5	3
Okeechobee	20673.29	10411.13	644.9694	6.204233	21963.76	34603.53	1
Orange	57335.35	29282.53	1778.477	6.07369	31811.37	863940.7	6
Osceola	36646.36	16727.13	1021.059	6.104767	24158.16	165384.4	2.529412
Palm Beach	32372.08	17534.09	1074.839	6.13022	52725.27	1088197	5.764706
Pasco	17650.24	9461.47	586.7697	6.202692	27018.41	340563.4	5
Pinellas	32679.1	14643.28	893.7375	6.103032	37300.62	903520.9	4.882353
Polk	34774.55	13462.44	818.6117	6.081534	28315.98	474401.1	7.235294
Putnam	23628.13	8399.57	514.6966	6.12999	22322.99	70101.41	1
Santa Rosa	14652.06	6615.674	423.952	6.402334	29667	112728.1	1.529412
Sarasota	30773.64	17452.22	1072.142	6.141991	46629.65	321296	1.647059
Seminole	32455.05	15989.99	976.5369	6.107257	36584.29	353126.3	3.176471
St. Johns	22398.1	13640.53	840.6987	6.162915	43700.38	119129.6	1
St. Lucie	21316.39	10681.33	656.9963	6.151947	26857.3	192475.8	2.176471
Sumter	16577.97	6792.993	429.1202	6.322923	20506.01	49341.18	1
Suwannee	16688.54	7910.404	488.2501	6.171785	24441.75	33201.59	0.470588
Taylor	23166.89	11181.82	698.8429	6.256462	23021.44	18856.65	0.176471
Union	16391.3	3685.216	236.7302	6.426043	16388.58	12994.82	0
Volusia	24950.04	13398	824.2144	6.151837	28423.29	433245.2	6
Wakulla	10232.04	4195.135	274.9388	6.568693	25137.83	21191.53	0
Walton	25215.91	16923.45	1051.674	6.209774	25416.25	38854.94	1
Washington	11348.36	5327.468	348.9188	6.542852	21634.66	20013.65	0.705882

Note: Mean of all the 17 years by county.

As mentioned above we estimate using both OLS and IV approach. Table-3 reports the results from OLS estimation whereas table-4 reports the results from the IV estimation. The

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OLS results in table 3 shows that per capita personal income has significant effect on per capita retail sales, taxable retail sales and revenue from sales tax. In particular, if income increases by $1 in a county total sales increase by approximately 54 cents, sales tax base (total taxable sales) increases by 41 cents, and total sales tax increase by approximately 3 cents. Sales tax rate is not affected by income. Because of a Wal-Mart, total retail sales in a county increase by $50 million but sales-tax base (total taxable sales) decreases by approximately $5 million, sales-tax revenue decreases by $400 thousand. Moreover, a Wal-Mart in a county decreases the sales-tax rate by .05 percentage points. Of these effects of Wal-Mart, the effects on total sales and sales tax rate are statistically significant.

The IV estimation shows that income has significant effect on total sales, tax base and sales-tax revenue as before. However, in IV estimation, Wal-Mart no more increases total retail sales statistically significantly. Because of a Wal-Mart, total retail sales in a county increase by $45 million but the effect is not statistically significant. Because of a Wal-Mart, sales tax base (total taxable sales) in a county decreases by $14 million and total sales-tax revenue decreases by $64 thousand. None of these effects are also statistically significant. However, because of a Wal-Mart, sales tax rate decreases by 0.23 percentage points and this effect is statistically significant.

Either local governments commit to reduce sales-tax rate to attract Wal-Mart especially when two nearby localities are competing for a Wal-Mart store or Wal-Mart may have influence over local governments' decision making. Moreover, because of a Wal-Mart the sales of low-tax commodities may increase more relative to high-tax commodities which may ultimately affect the gross sales tax rate.

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Table 3.3: OLS Estimation

	Total Retail Sales	Sales Tax Base (Total Taxable Sales)	Total Sales Tax	Sales Tax Rate
Per Capita Income	0.5390***	.4088***	.0252***	-.0000
Wal-Mart	50000000**	-4853430	-409121	-.0488***
R^2	.42	.60	.62	.10
No. of Observation	1138	1138	1138	1138

Note: Robust standard errors are considered. ***, **, * imply significant at 1%, 5%, and 10% level of significance respectively.

Table 3.4: IV Estimation

	Total Retail Sales	Sales Tax Base (Total Taxable Sales)	Total Sales Tax	Sales Tax Rate
Per Capita Income	.2380***	.1905***	.0122***	.0000
Wal-Mart	45000000	-14000000	-64220	-.2304*
R^2	.13	.37	.39	.07
No. of Observation	1138	1138	1138	1138

Note: Robust standard errors are considered. ***, **, * imply significant at 1%, 5%, and 10% level of significance respectively.

3.6 CONCLUSION

This study has evaluated the impact of entry of Wal-Mart on the total retail sales, taxable retail sales, revenue from sales tax and sales tax rate in Florida. Whether to allow Wal-Mart in a locality or not is an issue of immense debate. In most of the localities, Wal-Mart is allowed to open a store with the hope that it will boost local economic activities and tax-revenue in the area in addition to selling groceries and other commodities cheap to the local consumers. However, analyzing county level data from Florida, we find that it is not necessarily true that Wal-Mart boosts local economic activities by increasing total retail sales, and that Wal-Mart increases local sales-tax revenue. Furthermore, we find that the presence of Wal-Mart significantly help decrease local sales-tax rate. Wal-Mart's effect on sales tax rate is robust to both OLS and IV

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estimation. Either local governments commit to reduce sales-tax rate to attract Wal-Mart especially when two nearby localities are competing for a Wal-Mart store or Wal-Mart may have influence over local governments' decision making. Further robustness of the findings warrants spatial expansion of the analysis.

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APPENDICES

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APPENDIX A: List of Agricultural Commodities

Banana, Barley, Beef, Cocoa beans, Coconut oil, Coffee (Robusta), Coffee (Other mild), Copra, Corn, Cotton, Fish, Fish meal, Groundnut, Groundnut oil, Hard logs, Hard Swan, Hides, Jute, Lin seed oil, Oat, Olive oil, Orange, Palm oil, Peanut oil, Pepper, Plywood, Poultry, Rapeseed oil, Rice, Rubber, Shrimp, Sisal, Soft logs, Soft swan, Sorghum, Soybean meal, Soybean oil, Soybeans, Sugar (Europe), Sugar (Free market), Sugar (US market), Sunflower oil, Swine, Tea, Tobacco, Wheat, Wheat (red), Wood pulp, Wool, Wool (fine).

Other commodities: West Texas Intermediate (WTI) crude oil, Potassium Chloride.

APPENDIX B

Table 1: Correlation Matrix

	Corn Price	Oat Price	Wheat Price	Soybean Price
Real Interest Rate	-.38	-.53	-.34	-.63
Inventory	-.36	-.50	-.46	-.33
Global Demand	.16	.25	.11	.27
REER	-.48	-.22	-.45	-.33

Note: All the variables are in real term and in logarithmic form (except interest rate).

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APPENDIX C: Impulse Response Functions of Individual Commodities.

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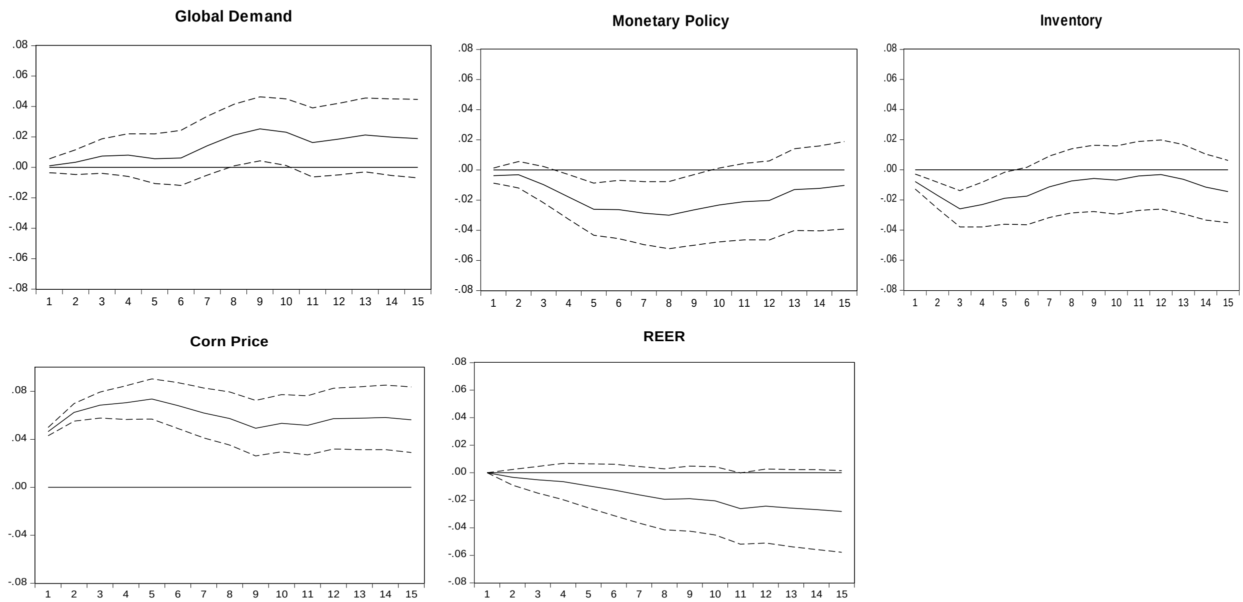
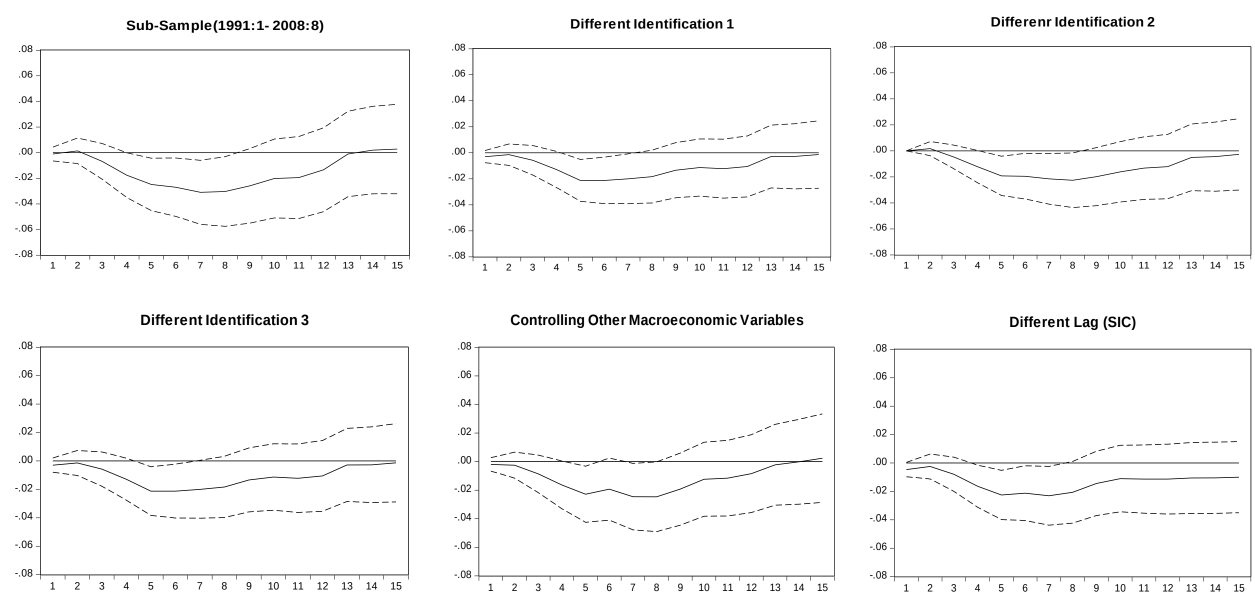
Impulse Response of Corn Price to one standard deviation shock to



Note: The horizontal axis reports the months after the shock.

Fig 1: Impulse Response of Corn Price. Dotted lines are 90% confidence interval



Note: The horizontal axis reports the months after the shock.

Fig 2: Robustness check for the effectiveness of monetary policy on corn price. (Impulse Response of Corn Price to monetary policy shock. Dotted lines are 90% confidence interval).

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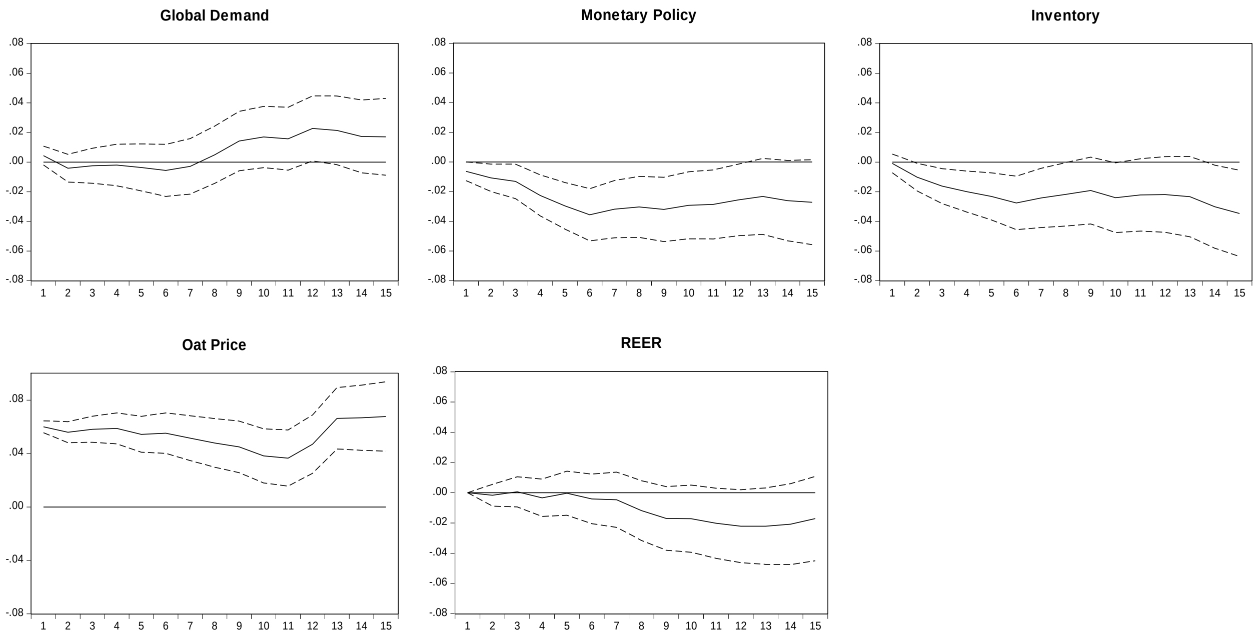
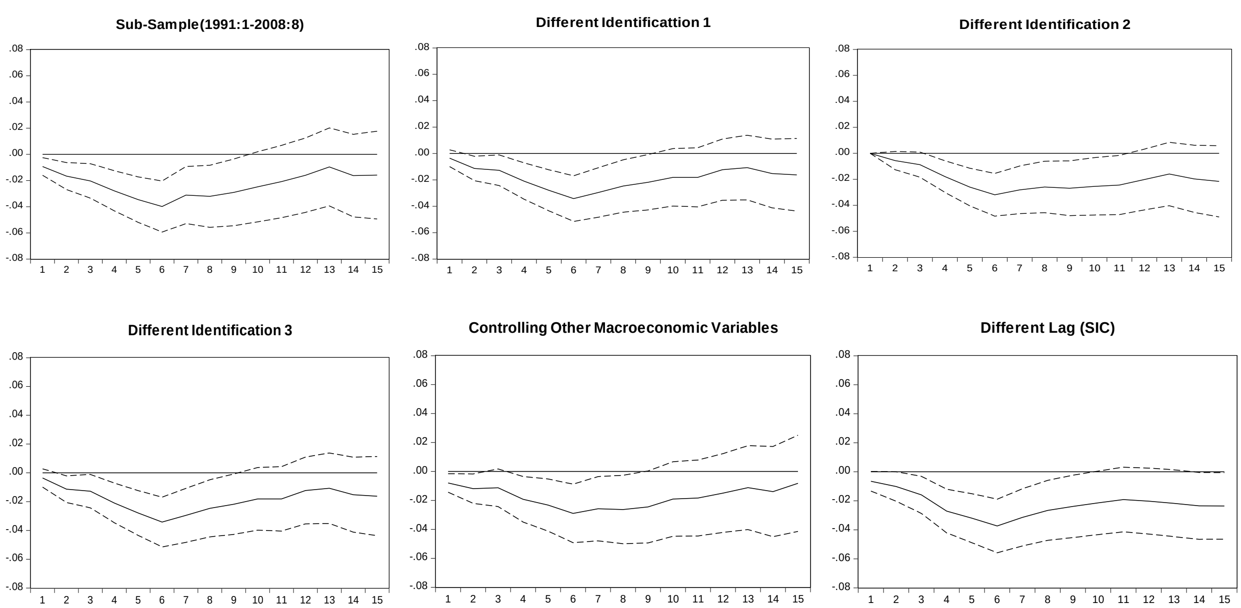
Impulse Response of Oat Price to one standard deviation shock to



Note: The horizontal axis reports the months after the shock.

Fig 3: Impulse Response of Oat Price. Dotted lines are 90% confidence interval.



Note: The horizontal axis reports the months after the shock.

Fig 4: Robustness check for the effectiveness of monetary policy. (Impulse Response of Oat Price to monetary policy shock. Dotted lines are 90% confidence interval.)

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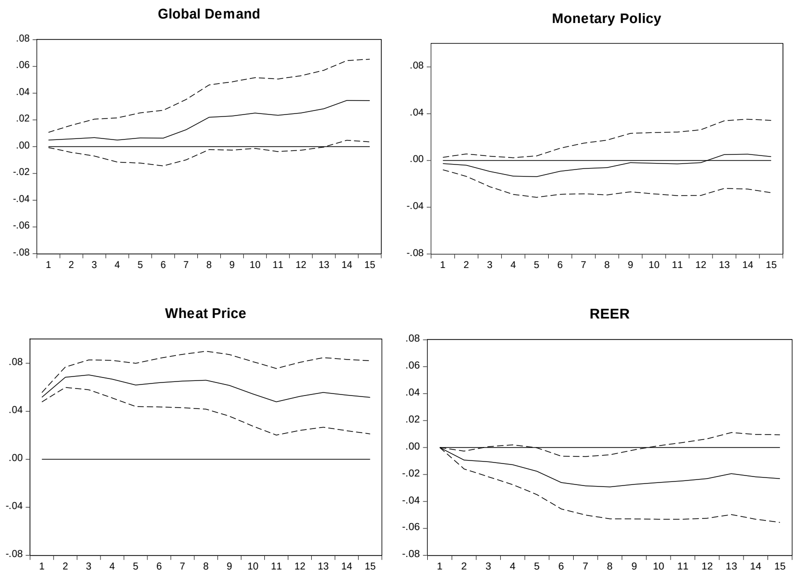
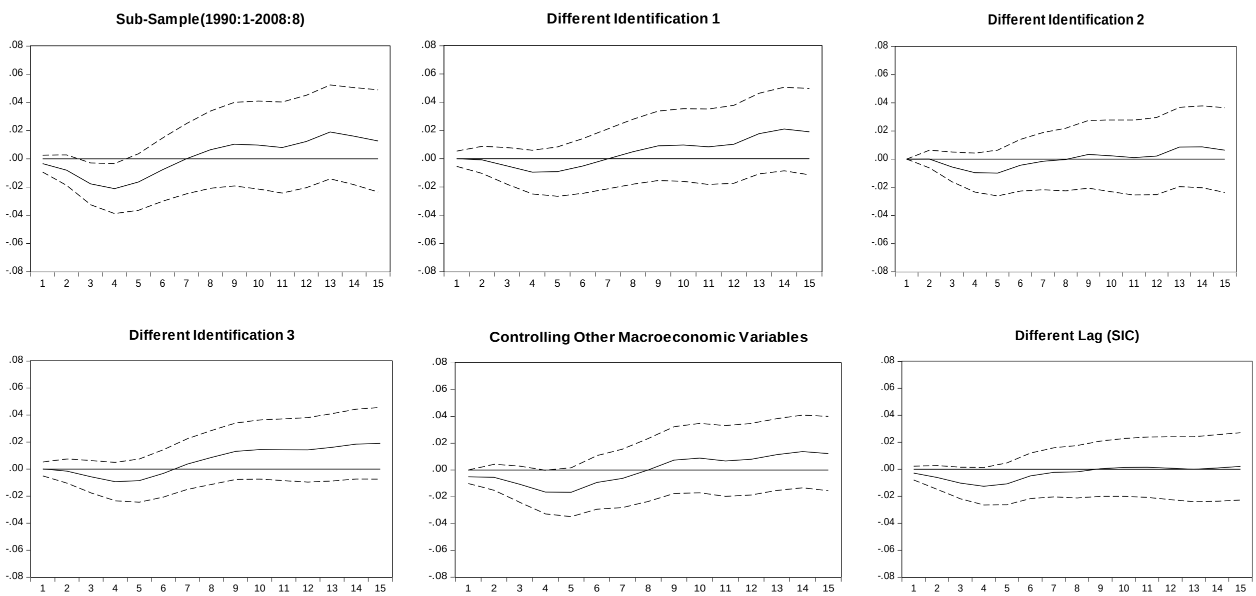
Impulse Response of Wheat Price to one standard deviation shock to



Note: The horizontal axis reports the months after the shock.

Fig 5: Impulse Response of Wheat Price. Dotted lines are 90% confidence interval.



Note: The horizontal axis reports the months after the shock.

Fig 6: Robustness check for the effectiveness of monetary policy. (Impulse Response of Wheat Price to monetary policy shock. Dotted lines are 90% confidence interval.)

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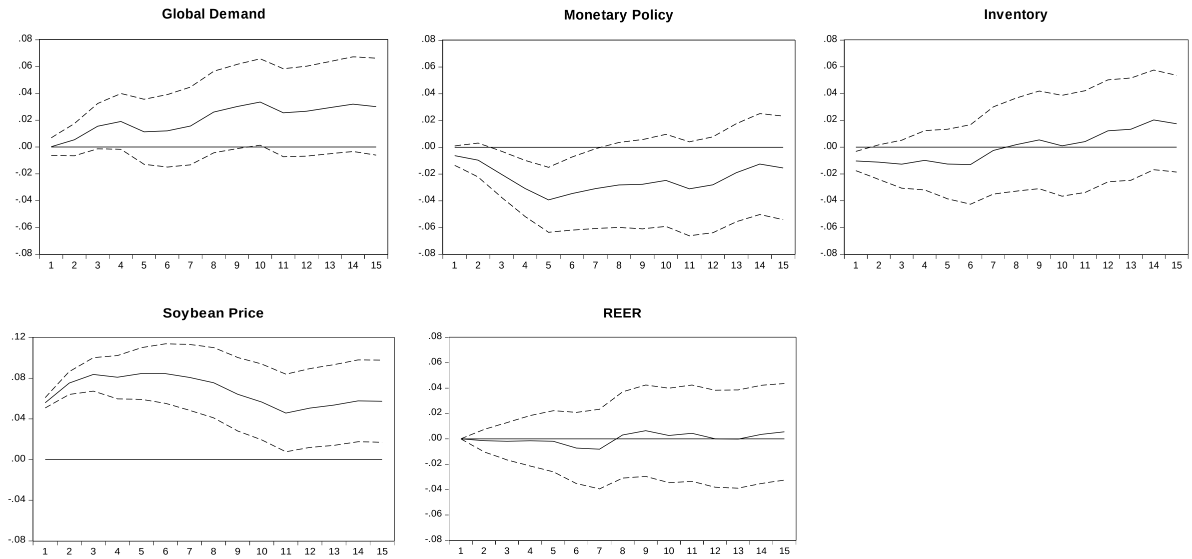
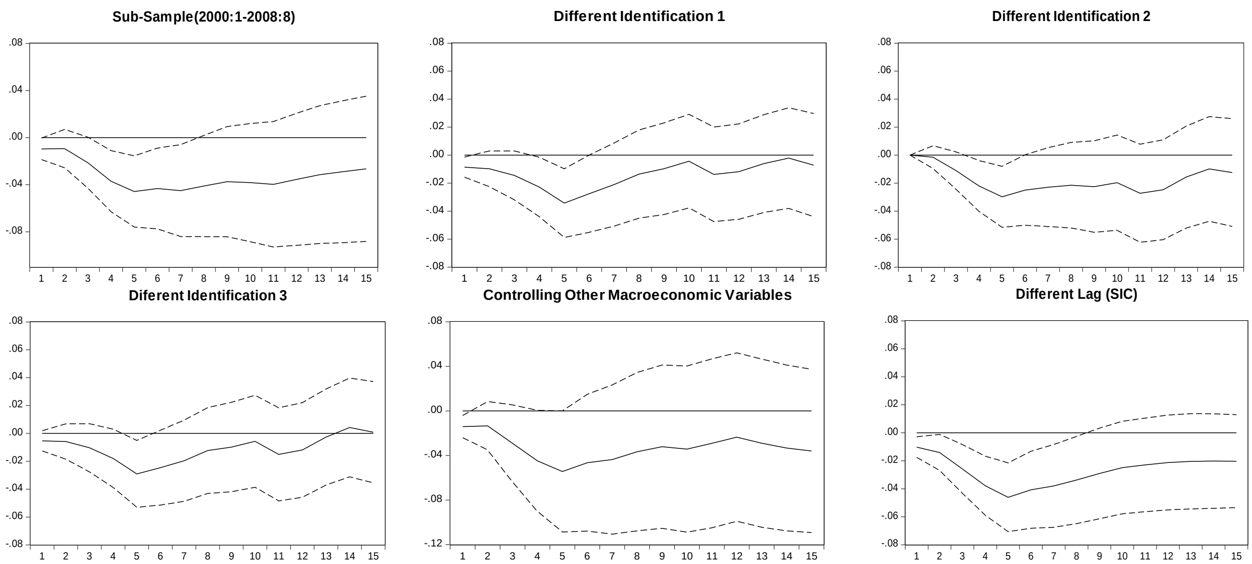
Impulse Response of Soybean Price to one standard deviation shock to



Note: The horizontal axis reports the months after the shock.

Fig 7: Impulse Response of Soybean Price. Dotted lines are 90% confidence interval[48].



Note: The horizontal axis reports the months after the shock

Fig 8: Robustness check for the effectiveness of monetary policy. (Impulse Response of Soybean Price to monetary policy shock. Dotted lines are 90% confidence interval.)

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[48] The sample is from 2000:m1 as inventory data before that are not available.

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APPENDIX D

Table 2: Factor Loadings/Percentage of variance explained by the common factor.

	Loadings (Percentage of Variance explained by common factor)			
	1991:1-2002:12	1991:1-2008:8	1991:1-2014:5	2003:1-2014:5
Barley	0.22	0.25	0.23	0.21
Cocoa beans				0.1
Coconut oil	0.21	0.24	0.24	0.24
Coffee (Other mild)			0.11	0.16
Coffee (Robusta)		0.1	0.1	0.14
Copra	0.2	0.23	0.23	0.23
Corn	0.34	0.29	0.28	0.23
Cotton		0.13	0.15	0.16
Fish (Salmon)				0.1
Groundnut				0.1
Groundnut oil		0.14	0.1	0.1
Sawn wood				0.1
Lamb				0.11
Lin seed oil	0.11	0.14	0.14	0.14
Oat	0.14	0.13	0.12	0.11
Palm oil	0.23	0.25	0.25	0.25
Peanut oil		0.15	0.11	0.1
Rapeseed oil	0.11	0.16	0.18	0.21
Wheat (Red)	0.25	0.18	0.2	0.17
Rubber		0.16	0.17	0.18
Sisal		0.1		0.11
Sorghum	0.33	0.25	0.24	0.2
Soybean meal	0.23	0.24	0.24	0.21
Soybean oil	0.34	0.32	0.32	0.29
Soybean	0.34	0.32	0.31	0.27
Sugar (Free market)		0.12	0.12	0.16
Sugar (US market)	0.26	0.13	0.15	0.1
Wheat	0.27	0.21	0.22	0.18
Wood pulp				0.12
Wool		0.13	0.14	0.19
Wool fine			0.12	0.2

Note: We only report the commodities which have loadings greater than 0.10 for at least one of the sample periods.

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Appendix E: Impulse Response Functions of the Common Factor.

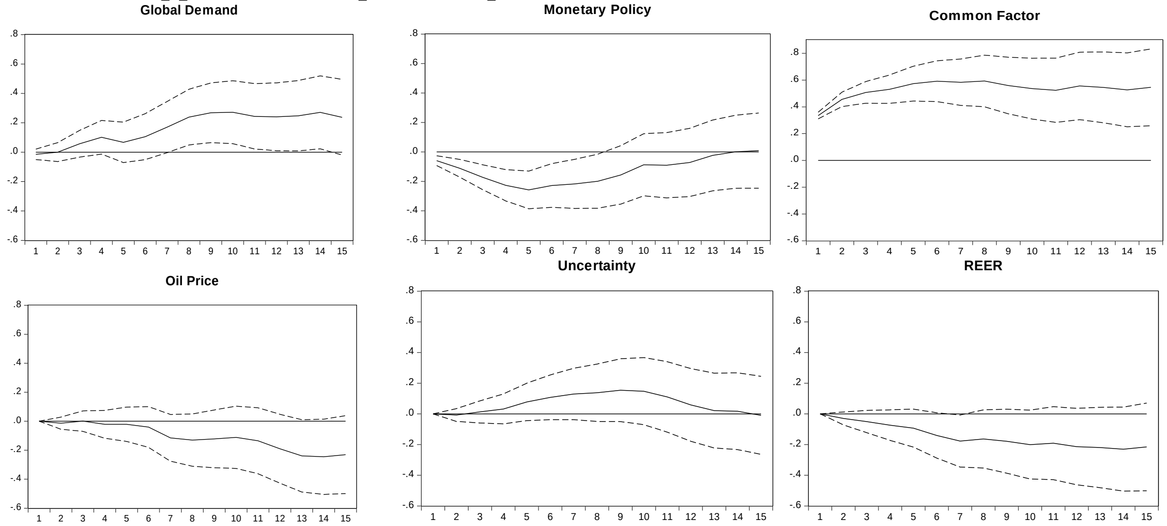

Fig 9: Impulse Response of the common factor. Dotted lines are 90% confidence interval.
Impulse Response of 'Common Factor' to one standard deviation shock to

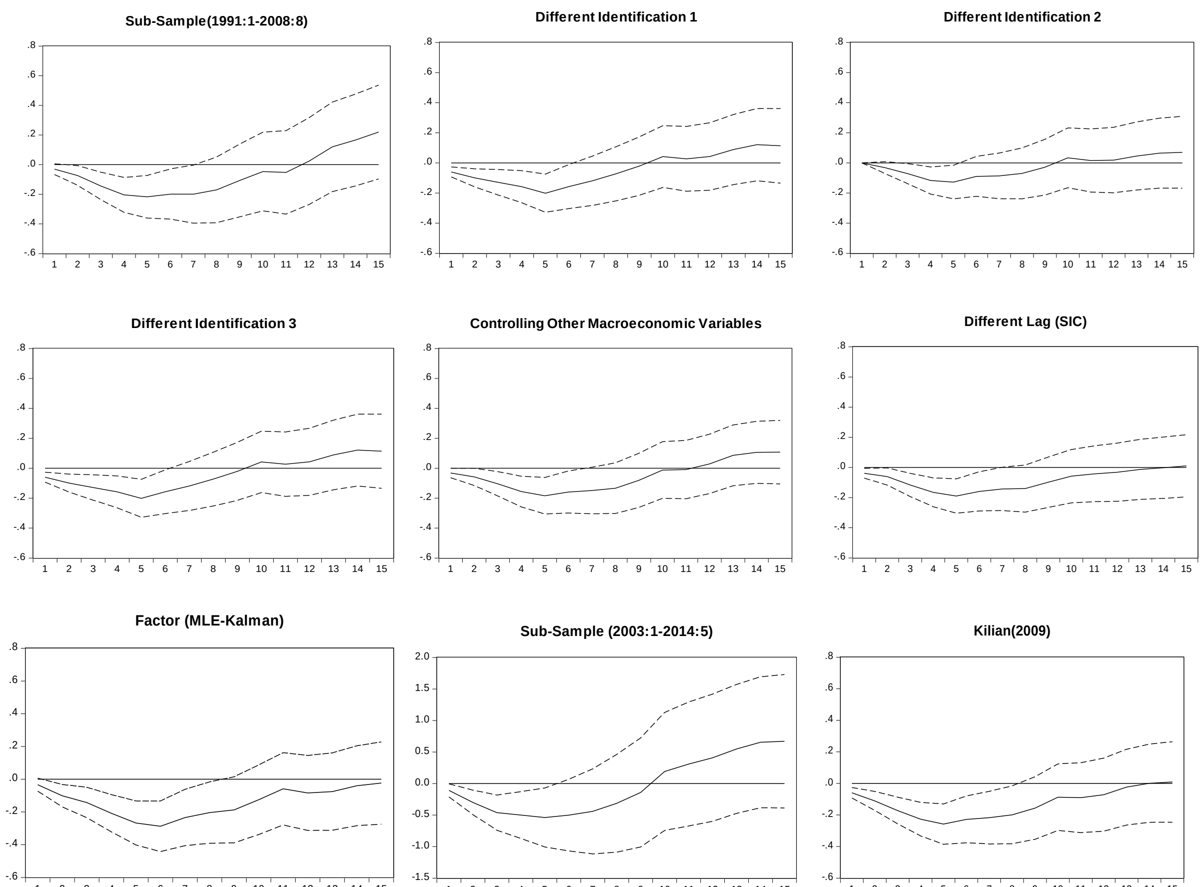

Fig 10: Robustness check for the effectiveness of monetary policy. (Impulse Response of 'common factor' to monetary policy shock. Dotted lines are 90% confidence interval.)

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VITA

Graduate School

Southern Illinois University

Md Rafayet Alam

mailtorafayet@gmail.com

University of Chittagong

Bachelor (Economics), May 2003

The Australian National University

Masters (International and Development Economics), December 2012

Special Honors and Awards:

Australian Government Scholarship, Spring 2011-Fall 2012

Dissertation Title: Macroeconomic Aspects of Commodity Price Dynamics

Major Professor: Dr. Scott Gilbert and Dr. AKM Mahbub Morshed

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