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The Impact of Remittances Versus Parental Absence on Children's Wellbeing: Evidence from Rural Punjab

Nida Jamil*

Abstract

This study examines the impact of migration on children left behind in terms of schooling and child labor by quantifying two aspects of migration: remittances and parental absence, in cases where the father is the migrant. The study is based on a panel analysis of data drawn from the Multiple Indicator Cluster Survey for 2007 and the Privatization in Education Research Initiative survey for 2011. The sample comprises 820 households with children aged 5–14 years. The study uses the instrumental variable (IV) approach due to endogeneity. Exogenous variation in parental absence and remittances sent by migrants from a given kinship network are employed as IVs. This, combined with household fixed effects and random effects, increases the reliability of the results. While remittances benefit the children, father's absence has adverse consequences for them. However, mother's presence in the house appears to compensate for the father's absence, making the migration beneficial on net for the child. The father's absence has worse consequences for girls in terms of increased child labor, where the money coming in through remittances has a larger impact on boys' schooling.

Keywords: Migration, remittances, schooling, child labor, mother presence, Pakistan.

JEL classification: F24, O15.

1. Introduction

This study examines the impact of migration on children's wellbeing with a focus on child labor and education in rural Punjab. While most studies focus on the impact of remittances and (migrant) parental absence as separate aspects, this research combines the two with respect to their collective effect on children left behind.

The World Bank reports that, in 2012, 22.3 percent of Pakistan's population still lived below the poverty line; the country is also ranked among the world's lowest spenders on education (around 2 percent of its

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GDP).[1] According to International Labor Organization (ILO) estimates, over 200 million children in the world are engaged in child labor. In Pakistan, 3.8 million children aged 5–14 years are economically active, a third of whom have never been enrolled in school.[2] In most cases, children engage in child labor to help support their families. Milligan and Bohara (2007) note that poor households resort to child labor and reduced schooling as a way of dealing with economic shocks. In such cases, child labor displaces education, thereby lowering future returns to labor for children over their lifespan, which ultimately worsens poverty levels in that country.

I examine the role of migration, focusing on households in which the father has migrated for work, to determine the net impact of remittances and paternal absence on children. Migration in this context includes both international and domestic migration, both of which imply, from the child's perspective, that the father is absent. The impact of migration is likely the twofold impact of the positive benefits associated with remittances and the negative effect of parental absence. Assessing the impact of either component separately – which is what much of the existing literature does – fails to provide a holistic picture of the net impact of migration on children. While remittances help to ease the financial constraints of poor households, the absence of a family member (particularly the father) may create an excess burden of work along with emotional consequences, leaving children worse off overall. Thus, while remittances ease the budget constraint, leading to a decrease in child labor and an increase in schooling, parental absence may reduce the overall positive impact.

This study asks to what extent the total effect of migration can be decomposed into the monetary benefit of remittances and the loss resulting from the father's absence. Formally, a panel analysis is carried out using the instrumental variable (IV) approach, combined with household fixed effects (HFE) and random effects (RE), focusing on children aged 5–14 years in rural Punjab. The study deals explicitly with the problem of endogeneity with respect to remittances and the father's absence by using separate kinship group IVs for both. For the latter, the kinship network refers to the fraction of households belonging to a given kinship group, in a given district, that include a migrant, excluding household *j*. Similarly, for remittances, the kinship network refers to the fraction of households belonging to a given kinship group, in a given district, that receive remittances, excluding household *j*. These instruments use the variation over time in the migrant

[1] http://info.worldbank.org/etools/docs/library/237384/toolkitfr/pdf/facts.pdf
[2] http://www.ilo.org/islamabad/areasofwork/child-labour/lang--en/index.htm

network to which a particular household belongs. Combining the IV approach with RE and HFE increases the reliability of the results.

The results indicate that the inflow of remittances benefits the school enrollment of the child. After controlling for time-invariant factors at the household level, remittances increase the probability of the child being enrolled in school by 20 percentage points. The money coming in through remittances also reduces child labor by lowering the opportunity cost of schooling because it decreases the marginal utility of income. In this context, the results indicate that, in developing countries such as Pakistan, remittances are spent not only on consumption goods, but also on productive investments in human capital development. On the other hand, the father's absence has a strong impact on child labor, increasing its probability by 27 percentage points. The money coming in from remittances does not necessarily offset the negative impact of the father's absence, mainly because the child is now subject to a larger work burden and less parental monitoring. However, if the child's mother is at home, the negative effect of the father's absence disappears, as she is there to share the burden of work and monitor the child.

There is also a gender differential when one looks at how the money remitted is spent: boys' schooling is favored over that of girls. Remittances increases the probability of boys being enrolled in school increases by 25 percentage points; the corresponding result for girls is 18 percentage points. Remittances also tend to favor boys over girls in terms of reducing child labor. The results suggest that, as more money comes in, boys are substituted away from child labor toward schooling – perhaps because they are seen as future breadwinners for their family. However, the father's absence only affects girls in terms of reduced schooling. Girls are more likely to engage in household work, but both genders may be compelled to work, particularly in cases where the mother is absent.

The study is organized as follows. Section 2 briefly reviews the existing literature. Section 3 describes the datasets used. Section 4 presents some descriptive statistics. Sections 5 and 6 describe the methodology used, followed by a discussion of the results. Section 7 concludes.

2. Literature Review

On the applied side, various studies have been carried out to assess the impact of migration on the household of origin, particularly on the children the migrant leaves behind. Most of this work focuses on the impact of migration through remittances or parental absence alone. The reported impact of remittances and parental absence is mixed. While much of the literature is consistent with the idea that remittances ease the household's financial constraints, thereby improving the situation of children left behind in terms of increased schooling and reduced child labor (see Edwards & Ureta, 2003; Calero, Bedi & Sparrow, 2009; Alcaraz, Chiquiar & Salcedo, 2012), some studies argue that remittances may increase child labor if the money received gives the household a chance to start a new business. Similarly, others conclude that parental absence compels children at home to shoulder an excess work burden; this, along with the lack of monitoring, leaves them worse off (Grogger & Ronan, 1995; Lang & Zagorsky, 2001; Milligan & Bohara, 2007). Finally, some studies point out that migrant parents may be more aware of the importance of education and thus encourage their children's schooling.

Hanson and Woodruff (2003) examine the impact of remittances on educational attainment in Mexico in terms of accumulated schooling. They test whether children from households with an external migrant complete more years of schooling than their peers. The authors conclude that remittances do increase schooling for left-behind children, but only in households where the parents are not highly educated. Supporting this conclusion, Bayot (2007) argues that Mexican households receiving remittances enjoy a better quality of life: the money coming in eases the household's budget constraint, giving it the chance to substitute children away from child labor and toward schooling.

Using historical migration rates to instrument for migration in Punjab, Arif and Chaudhry (2015) find that remittances have a positive effect on children's schooling outcomes, measured by enrollment, accumulated levels of schooling, the number of days spent in school and lower dropout rates. Several studies have attempted to take this a step further by disentangling the impact of remittances by gender. In a study on Jordan, Mansour, Chaaban and Litchfield (2011) find that, after controlling for the socioeconomic determinants of schooling, remittances improve educational attainment and attendance.

This result holds more strongly for boys than for girls, given that, in most developing countries, sons are seen as future breadwinners and parents thus have incentives to invest more in them. Based on data for Nepal, Vogel and Korinek (2012) conclude that remittances are spent disproportionately on boys, while girls benefit only if they belong to a higher-income household. Mansuri (2006) finds, however, that remittances may reduce gender inequality by benefiting both genders. Using migration networks as an IV to control for simultaneity bias, her work on rural Pakistan shows that remittances reduce gender inequalities in access to schooling, with a greater and significant impact on girls' schooling.

Other studies have focused on the negative aspect of migration and argue that the positive effect of remittances is, in many cases, offset by the negative effect of the migrant's absence, especially if one or both of the child's parents is a migrant (Grogger & Ronan, 1995; Lang & Zagorsky, 2001). In Sri Lanka, for example, many mothers migrate overseas to earn a better livelihood for their families. In such cases, their absence generates loneliness among left-behind children. In the long term, a sense of family disunity and lack of communication between child and mother can leave the former harmed psychologically, with adverse consequences for his/her schooling performance (Ukwatta, 2010).

The absence of a migrant father often means that children have no male role model. In a study on Swaziland, Booth (1995) finds that women whose husbands had migrated overseas complained they could not manage their children's behavior or schooling. Further, with one parent – in most cases, the father – gone abroad, the mother's workload at home increases, leaving her less time to spend with her children and making her more "unavailable" to them. Milligan and Bohara (2007) point out that remittances can also create a moral hazard problem if families who receive remittances choose to invest the money in risky business projects, compelling their children to seek work rather than remaining in school in the migrant's absence.

This study is closest to the approach of Amuedo-Dorantes and Pozo (2010), who assess the impact of remittances and migrant absence on children left behind. The authors focus on migration from the Dominican Republic to the US. Initially, they divide their data into migrant and nonmigrant households. The dataset is such that most of the children in the sample – and most children whose families receive remittances – belong to a nonmigrant household (one that receives remittances from a relative who is not considered part of the immediate family). The first part of the analysis deals with nonmigrant households, which allows the authors to isolate the impact of remittances from that of migrant absence. The analysis is then repeated to include children living in migrant households and the results compared. As an IV, the study uses US unemployment rates for 1999/2000 along with average real earnings for those areas (in the US) where Dominican migrants have settled. They conclude that remittances have a positive impact on schooling when using the nonmigrant household sample, but observe that this declines on taking into account the negative impact of migration by using the entire sample. Child labor increases concomitantly. Children may engage in market activities to support migration expenses, leaving them less time for school. They may also have to assume responsibility for household chores in the absence of an adult family member.

The present study's objective is to build on the literature in several important ways. First, it seeks to identify the total effect of migration, i.e., the collective impact of remittances and parental absence. It separates these two effects quantitatively, which most other studies do not. Unlike Amuedo-Dorantes and Pozo (2010), all the recipient households in the sample used include a migrant member. Moreover, rather than using one IV as the authors have done for both samples,[3] this study makes a stronger case by using two separate IVs: one for remittances and one for paternal absence. While Amuedo-Dorantes and Pozo do not distinguish between migrant household members, I have focused on migrant fathers per se to capture the impact of parental absence. Second, the study looks at both dimensions of children's wellbeing: child labor status and schooling status. In doing so, it deals explicitly with the issue of endogeneity with respect to remittances and the father's absence. The study builds a panel analysis using an IV approach combined with HFE. Third, the study uses kinship networks as an instrument on the assumption that the close association among kinship groups (which can include migrants) is likely to serve as a source of knowledge about migration and remittances: this, in turn, may encourage prospective migrants. Finally, this study is the first to identify the joint quantitative impact of remittances and parental absence in Pakistan's case.

3. Datasets

Two datasets were used to create a panel. The first was taken from the Punjab government's Multiple Indicator Cluster Survey (MICS), which was conducted at the tehsil and district level in 2007. The second dataset was from a survey funded by the Open Society Institute's Privatization in Education Research Initiative (PERI). Conducted in 2011 by the Lahore School of Economics in collaboration with the Punjab Bureau of Statistics, the PERI survey sampled eight rural tehsils of Punjab in seven districts. The dataset includes 1,024 rural households who had previously been interviewed as part of the MICS.[4]

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[3] Although differences between samples can be endogenous.

[4] See http://www.creb.org.pk/Data%20PERI. The districts covered include Bahawalpur, Faisalabad, Jhang, Hafizabad, Nankana Sahib, Khanewal and Chakwal.

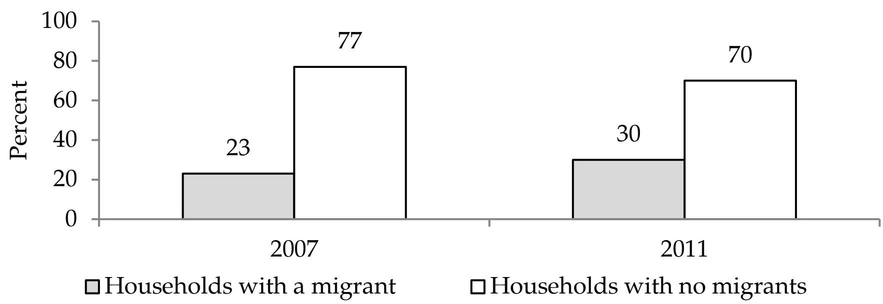
For the purposes of this study, children fall within the 5–14-year age bracket. After cleaning the data, a panel of 820 households remained. This panel was constructed at the rural household level, allowing MICS households to overlap with those from the PERI dataset. However, the same children within the household might not overlap because the panel was not constructed at the individual level. Thus, it was not necessary for one child to remain part of the analysis in both rounds. Any child who fell within the 5–14 age cohort at the time of the survey was included in the sample for that year. Since this is an unbalanced panel, children who fell within the age bracket of 5–14 were included in the first round if they were still part of this age bracket in the next round. However, children who had passed 14 by 2011 were excluded from the sample for that year.[5]

We observe the child labor and schooling outcomes of those children who fell within the 5–14 age bracket at the time of the survey. Thus, 1,382 children fell within this cohort in 2007 (MICS) and 1,581 children fell within the cohort in 2011 (based on 820 PERI households). About 62 percent of these children overlapped and were thus part of both rounds; the remaining children were part of either the MICS or PERI datasets only.

4. Descriptive Statistics

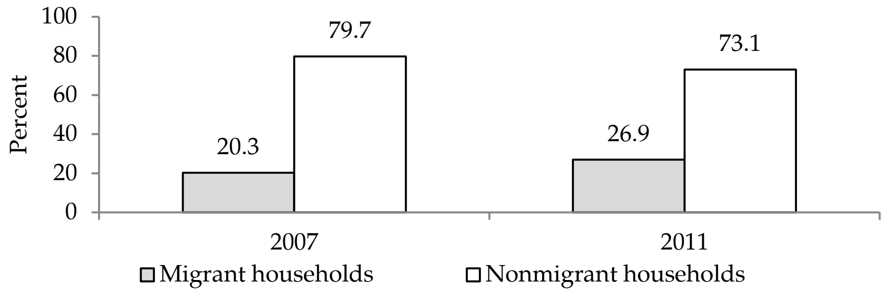
Figure 1 shows what proportion of households included a migrant in 2007 and 2011. Clearly, migration increased between these years. Figure 2 gives the distribution of children who belonged to a migrant or nonmigrant household in 2007 and 2011.

Figure 1: Migrant and nonmigrant households



[5] A child who was five years old in 2007 was nine years old in 2011. Since s/he falls within the 5–14 age bracket in both years, s/he will be included in both rounds. On the other hand, a child who was 14 years old in 2007 was 18 years old in 2011. S/he is, therefore, part of the 2007 sample, but not part of the 2011 sample.

Figure 2: Children from migrant and nonmigrant households



In Figure 3, we see the percentage of children whose fathers were absent. The father's absence is explained by (i) migration, (ii) the dissolution of the family unit as a result of separation or divorce, or (iii) death.

Figure 3: Distribution of children, by father's presence

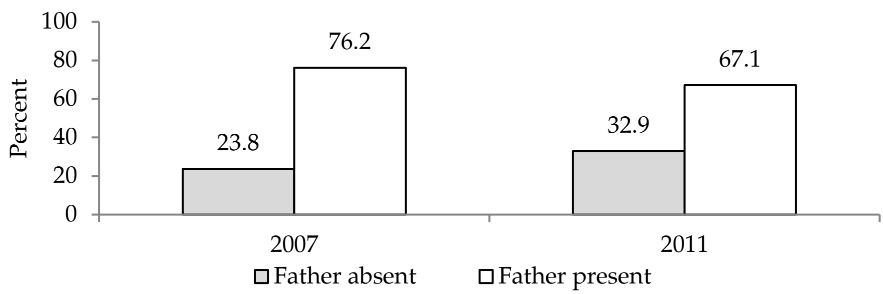


Figure 4 gives the distribution of children by their mother's status. Figure 5 shows that migration does not account for the mother's absence in either year, which leaves either death (applicable in most cases) or divorce/separation as the reason for her absence from the household.

Figure 4: Distribution of children, by mother's presence

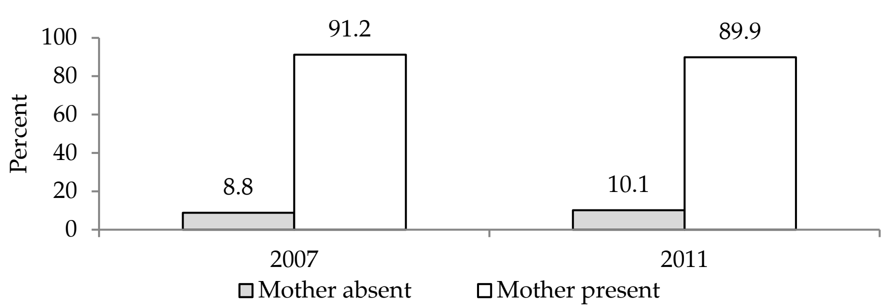


Figure 5: Reasons for mother's absence as a percentage of children whose mother is absent

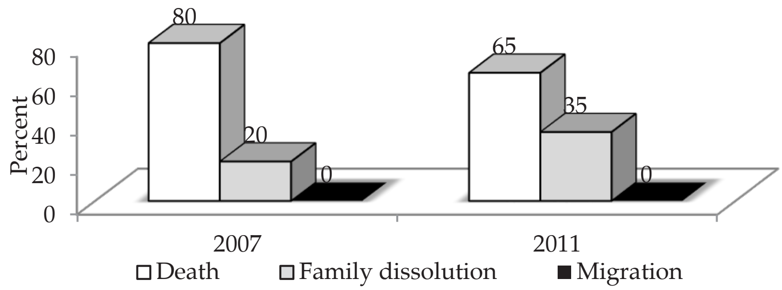


Table 1 gives the percentage of recipient households and the distribution of remittances between domestic and international sources. The table indicates an increase in the number of households receiving remittances, the bulk of which originate from within Pakistan. Table 2 shows that, between 2007 and 2011, the number of non-working children going to school increased. "Work" includes any labor carried out at home as well as outside. The "work and school" and "work only" categories register a decline for both genders.

Table 1: Distribution of households, by receipt and type of remittances

	Percentage of households	
Remittances received	**2007**	**2011**
No	84.00	81.00
Yes	16.00	19.00
Type of remittances		
Domestic remittances only	75.00	73.68
International remittances only	18.75	21.05
International and domestic remittances	6.25	5.27

Source: Author's calculations.

Table 2: Distribution of children, by activity

	2007		2011	
Activity	**Boys**	**Girls**	**Boys**	**Girls**
School only	65	25	70	29
Work and school	23	65	20	62
Work only	8	10	6	8
Neither	4	0	4	1

Source: Author's calculations.

Figure 6 shows that, of the total number of children working, 11 percent were engaged in work outside the home (whether paid or unpaid) in 2007; this declined to 7 percent in 2011.

Figure 6: Children engaged in nonhousehold labor as a percentage of the total number of working children

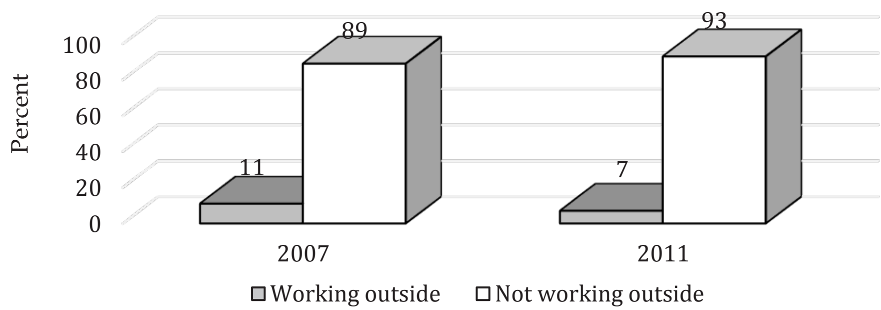
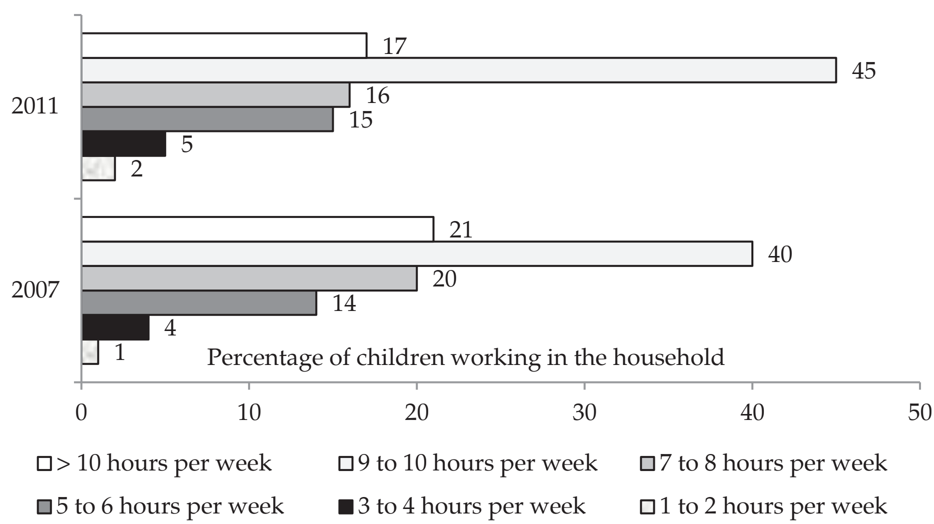


Figure 7 shows the percentage of children engaged in household work by the number of hours worked (those spending more than 10 hours a week carrying out household chores).

Figure 7: Percentage of children engaged in household labor, by hours worked in the last week



The figures and tables above show that trends in remittances, paternal absence, schooling outcomes and child labor outcomes have changed over time.

5. Methodology

Since the dependent variables are binary, we use a linear probability model (LPM) to estimate the specifications below. An LPM not only allows one to compare coefficients across groups and models, but it also enables intuitive interactions. It has the added advantage of giving coefficient results that are very close to their discrete counterparts when using dummy variables. The LPM also works well if one wants to estimate the average effect of a variable on any outcome of interest (Angrist, 2001).

There are several reasons for using an LPM over logit and probit models. While the latter make it easy to interpret estimated marginal effects (McGarry, 2000), they are more complicated to use than an LPM. Furthermore, probit models can entail the problem of perfect correlation (Reiley, 2005). Since the endogenous regressors are dummy variables, using a logit or probit model could be problematic (see Heckman, 1978). Despite being less commonly used, the LPM is at par in terms of classification and selection bias relative to logit and probit models (Chatla & Shmueli, 2013).

5.1. Main Specification

We begin with a simple LPM that estimates the impact of remittances and paternal absence on a child's welfare:

$$Y_{iht} = \beta_0 + \beta_1 X_{iht} + \beta_2 Z_{ht} + \beta_3 remittances_{iht} + \beta_4 father\ absent_{iht} + \varepsilon_{iht} \quad (1)$$

where the child is denoted by the subscript i, the household by h and time by t. Y_{iht} is the dependent variable and takes four forms:

- $Schooling_{iht}$ is a dummy variable for child i in household h if he/she is currently enrolled in school at time t. Hence, if the child was "attending school" at the time of the survey, the variable equals 1 and 0 otherwise.
- $Overall\ child\ labor_{iht}$ is a dummy equal to 1 if child i has engaged in any kind of work, whether within or outside the home, in the past week, and 0 otherwise at time t. This follows the definition of child labor adopted by Binci and Giannelli (2012) where a child is deemed to have engaged in labor if s/he answers "yes" to at least one question relating to the last seven days' work. Thus, if child i has worked outside his/her home for someone or helped with household chores or

engaged in any family business (such as selling goods on the street) in the last week, the dummy equals 1 and 0 otherwise.[6]

- $Nonhousehold\ child\ labor_{iht}$ is a dummy equal to 1 if the child has engaged in any kind of work outside the home (that is, worked for someone who is not a member of the household) in the last week and 0 otherwise (see Figure 6).
- $Household\ child\ labor_{iht}$ is a dummy equal to 1 if the child has engaged in any kind of household chore for more than 10 hours in the last week and 0 otherwise[7] (see Figure 7).

Schooling and child labor decisions are a function of household and individual characteristics. X_{iht} is a vector of the child's characteristics at time t where child i belongs to household h. These include the child's age and gender (dummy variable equals to 1 if the child is a female), his/her father's education, mother's education and mother's presence. Z_{ht} denotes the characteristics of a given household h at time t. These include the household head's education, household size and wealth index.

Remittances is dummy variable which equals 1 if the child i belongs to household h which received remittances in the past year at time t. This includes both domestic and international remittances.

Father absent is a dummy equal to 1 if the father of child i is absent at time t and 0 otherwise. In this case, the father may be absent either as an international or domestic migrant. Since we cannot identify each migrant's exact location, it is not possible to determine whether the father has migrated overseas or within Pakistan. Moreover, we cannot measure how far away the father lives and, therefore, how often he visits home.

Finally, ε_{iht} is the time-varying or idiosyncratic error term representing unobservable factors that might affect the dependent variable. The standard errors are clustered at the district level.

5.2. *Specification Issues*

Simple ordinary least squares (OLS) will yield biased estimates. The error term and explanatory variables may be correlated as a result of omitted variables and selection bias, along with the problem of reverse causality. These issues are discussed in detail below.

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[6] UNICEF considers any work done inside the household to be a part of child labor.
[7] As defined in the ILO's global estimates of child labor (see footnote 2).

5.2.1. Endogeneity of the Remittances and Father Absent Variables and Selection Bias

Ideally, one would want to generate unbiased estimates by looking at the causal impact of remittances between recipient households and their outcomes in the counterfactual scenario where the same households do not receive remittances. However, since the households that receive remittances or have a parent absent due to migration are "self-selected" (based on their unobservable characteristics), households without migrants or those that do not receive remittances do not represent a suitable counterfactual.

Remittances are expected to ease the household's financial constraints, increasing schooling and reducing child labor. However, in situations where the migrant parent values education to the extent that he has chosen to migrate to provide better schooling for his child, it may be schooling that causes the inflow of remittances (e.g., a father might remit money home to reward a child who is doing well at school). In this case, schooling determines remittances, which creates a simultaneity bias in the estimates.

Hanson and Woodruff (2003) give the example of a father who has lost his job due to poor economic conditions and decided to migrate to seek better employment. Such adverse conditions may also force children at home to drop out of school and compensate for the father's absence by taking on extra household chores. The authors argue that poorer households may be less likely to send a member abroad and, at the same time, less likely to send their children to school. This creates bias in a simple OLS estimation.

The household's opportunities and connections can also bias estimates. Even unobservable characteristics such as the child's inherent ability, parents' perception of schooling and the motivation they provide their children can affect the left-hand-side and right-hand-side variables, creating endogeneity in the estimates. Adding the relevant controls does not solve the problem entirely because the unobservable variables will remain a concern. Thus, using OLS with observables added as controls will still yield biased estimates.

Given that adding controls does not address all these issues, we combine the IV approach with RE and HFE, instrumenting the endogenous variables to present two sets of results. The following section explains in detail how these approaches enable better estimates than simple OLS.

5.2.2. IV Approach with RE and HFE

In this case, kinship (or biraderi) networks serve as the instrument. We create separate IVs for remittances and the father's absence. The kinship network variable represents the fraction of households belonging to a given kinship group, in a given district, that receive remittances (excluding household *j*) at time *t*. Biraderi *B* denotes the different kinship groups and district *D* refers to the various districts. Thus, for *remittances*, the kinship network IV is the fraction of households belonging to a given kinship group, in a given district, that receive remittances, excluding household *j*.

$$\text{Remittances kinship (biraderi) IV} = \frac{\text{Number of households belonging to biraderi } B \text{ in district } D\text{, that receive remittances at time } t\text{, excluding household } j}{\text{Number of households belonging to biraderi } B \text{ in district } D \text{ at time } t}$$

For the *father absent* variable, the kinship network IV refers to the fraction of households belonging to a given kinship group, in a given district, that have had a family member migrate in the past, excluding household *j*.

$$\text{Migrant kinship (biraderi) IV} = \frac{\text{Number of households belonging to biraderi } B \text{ in district } D\text{, that have had someone migrate in the past, at time } t\text{, excluding household } j}{\text{Number of households belonging to biraderi } B \text{ in district } D \text{ at time } t}$$

These instruments help exploit variation over time in the migrant network to which a particular household belongs. This leads to exogenous variation in the likelihood of migrating as well as the amount of money being remitted. Although the father may be absent for several reasons, we can use the migrant biraderi IV to capture specifically the migration effect of his absence or the local average treatment effect (LATE).

The intuition behind constructing kinship network variables is that people who belong to the same biraderi and live in the same district are likely to associate closely with each other. Thus, the presence of migrants in a network might motivate others to migrate and send remittances to their family and friends back home. Current migrants often prove to be a source of information (in seeking jobs) and help (providing accommodation) for prospective or new migrants. Kinship association may also encourage remittance inflows when households belonging to the same biraderi in the same district see others receiving remittances and urge their own migrant members to do the same.

This entails the following first stage:

$$Remittances_{iht} = \mu_0 + \mu_1 X_{iht} + \mu_2 Z_{ht} + \mu_3 remittances\ biraderi\ IV_{ht} + \mu_4 migrant\ biraderi\ IV_{ht} + \nu_{iht} \quad (2)$$

$$Father\ absent_{iht} = \mu_5 + \mu_6 X_{iht} + \mu_7 Z_{ht} + \mu_8 remittances\ biraderi\ IV_{ht} + \mu_8 migrant\ biraderi\ IV_{ht} + \nu_{iht} \quad (3)$$

Next, we use the predicted values of *remittances* and *father absent* from the first stage in the original specification. Thus, the second stage is:

$$Y_{iht} = \alpha_0 + \alpha_1 X_{iht} + \alpha_2 Z_{ht} + \alpha_3 \widehat{remittances}_{iht} + \alpha_4 \widehat{father\ absent}_{iht} + \varepsilon_{iht} \quad (4)$$

We combine the IV estimates in turn with HFE and RE and compare the results to determine their robustness. RE is used when there is no omitted variable problem in the specification or when the omitted variables are believed to be uncorrelated with the model. This produces unbiased estimates and the smallest possible standard errors if all the data available is used. The key concern in using RE is that it will estimate the effects of time-invariant variables, but yield biased results if one does not control for omitted, unobserved time-variant variables. Thus, the study presents these results only as a robustness check to support the main argument, while basing the discussion and results on HFE, which is appropriate since it controls for time-invariant unobservable characteristics within a household. In this case, the subject is the control group itself, household *j*. Certain time-invariant factors may affect the household and will continue to affect it in the same way at later points (i.e., the effect remains constant).

Although biraderis will likely differ from one another in terms of entrepreneurial skills, ability and connectivity, the biraderi itself remains constant over time for a given household. This makes it possible to apply HFE controls for those dimensions of the biraderi that do not change over time. Since we are using a panel dataset, the IV numerator will be different in both periods for a single household *h* because its receipt of remittances and migration status will change over time. The net change will be exogenous, as variations in characteristics between biraderis do not drive the results. It is thus reasonable to argue that such changes in kinship networks are correlated with the receipt of remittances and migration for the reasons explained above. This renders the IV informative, but not with respect to household-level labor market decisions. An individual's knowledge of a migrant kinsman should not affect the schooling or child labor decision of child i. Thus, the instrument will affect schooling and child labor decisions solely through the remittances and migration channel.[8]

We apply the Hausman test after every specification as shown in the second-stage results (see Tables A2, A4 and A6 in the Appendix) to test the null that the RE estimator has the same coefficients as the consistent HFE estimator. If the coefficients are insignificant ($p > 0.05$), then we have the option of using RE. If the p-value is less than 0.05, we should rely on the HFE results instead.[9] We will see that the Hausman tests run also support the HFE results over the RE.

6. Extending the Main Specification

This section extends the main specification to find out whether the impact of *remittances* and *father absent* differs for girls and boys. It also looks at the extent to which the mother's presence might compensate for the father's absence.

6.1. Impact of Gender

The *remittances* and *father absent* variables interact with dummies denoting sons and daughters such that:

$$Y_{iht} = \alpha_0 + \alpha_1 X_{iht} + \alpha_2 Z_{ht} + \alpha_3 remittances_{iht} * male_{iht} + \alpha_4 remittances_{iht} * female_{iht} + \alpha_5 father\ absent_{iht} * male_{iht} + \alpha_6 father\ absent_{iht} * female_{iht} + \varepsilon_{iht} \quad (5)$$

$Male_{iht}$ is a dummy variable equal to 1 if child i is male and 0 if female. $Female_{iht}$ is a dummy variable equal to 1 if child i is female and 0 if male. Since $remittances_{iht}$ and $father\ absent_{iht}$ are endogenous, their

[8] We also test the validity of the instruments using the over-identification test (results available on request).

[9] The results tend to have a p-value below 0.05 in most cases, indicating that the HFE estimates are more reliable in this context.

interaction terms will also be endogenous. We instrument for these by constructing the following IVs:

Endogenous variable	**Instrument**
Remittances * male	Remittances biraderi IV_{ht} * male
Remittances * female	Remittances biraderi IV_{ht} * female
Father absent * male	Migrant biraderi IV_{ht} * male
Father absent * female	Migrant biraderi IV_{ht} * female

Interaction terms involving *remittances* and *father absent* in both cases (male and female) will allow us to look directly at which gender is affected more by remittances and by the father's absence.

6.2. Impact of Mother's Presence

We hypothesize that the negative impact of the father's absence is, to some extent, offset by the presence of the mother, who will presumably prevent the excess burden of work (associated with the father's absence) from falling solely on the child's shoulders and will also monitor the child's performance at school.

$$Y_{iht} = \phi_0 + \phi_1 X_{iht} + \phi_2 Z_{ht} + \phi_3 remittances_{iht} + \phi_4 father\ absent_{iht} + \phi_5 mother\ present_{iht} + \phi_6 mother\ present_{iht} * father\ absent_{iht} + \varepsilon_{iht} \quad (6)$$

Mother present is a dummy variable equal to 1 if the mother of child *i* in household *h* is at home at time *t* and 0 otherwise. This specification is identical to the main specification with the difference that it includes an interaction term comprising *mother present* and *father absent*. The coefficient ϕ_6 shows to what extent the presence of the mother offsets the impact of the father's absence on child *i*. Since the problem of endogeneity re-emerges, we instrument for *remittances*, *father absent* and *mother present* * *father absent*. This is done by creating an instrument for the term *mother present* * *father absent* by enabling *mother present* to interact with the migrant biraderi IV.

6.3. Mother Present as an Exogenous Variable

Mother present would have been endogenous had any mother in the sample been absent as a result of migration. However, in our case, *mother present* is exogenous because the sample does not contain any migrant mothers (see Figures 4 and 5). Mothers for whom this variable takes the value of 0 are absent either because they have died or because they are separated or divorced. This is not surprising, given that most rural women in Pakistan have restricted mobility both due to social norms and domestic responsibilities.

7. Results and Discussion

7.1. LPM Results of Main Specification

The results of the main LPM specification indicate that the inflow of remittances has a positive impact by increasing the probability of the child being enrolled in school (Tables A1 and A2). This suggests that money is an important component of the schooling decision and remittances are, to some extent, part of this. For households that receive remittances the probability of the child being enrolled in school increases by 20 percentage points (column 2). This result contradicts the body of literature suggesting that, in developing countries such as Pakistan, remittances merely increase consumption levels or expenditure on nondurable goods instead of promoting investment in human capital, such as in education (Amuedo-Dorantes & Mundra, 2007). Remittances are thus used by households to make productive investments and not used solely to meet consumption or basic subsistence needs.

Table A2 shows that remittances are also significant in reducing overall child labor since they ease the budget constraint for the households (column 4). This indicates that the money remitted benefits the household by increasing school enrollment as well as by reducing child labor. When the inflow of remittances eases the household's budget constraint, this reduces the child's overall work burden and lessens his/her responsibility for household work (if, for example, the household can now afford to hire help to carry out domestic chores or for childcare).

Additionally, the money coming in may be used to purchase labor-saving appliances, which free the child from having to carry out certain tasks; the installation of a gas stove, for instance, would reduce the need to collect firewood – a task that might otherwise have been assigned to the child. Households receiving remittances can compensate for the foregone income, thus lowering the opportunity cost of attending school. Remittances provide an alternative source of income, thus reducing the prevalence of child labor significantly at least within the household. The results suggest that remittances reduce the household's labor supply, particularly of children, by increasing the reservation wage of the remaining household members (see Danziger, Haveman & Plotnick, 1981).

The father's absence, on the other hand, seems to significantly affect both schooling and child labor outcomes adversely hence leaving the children worse off. Having a migrant father, a child is 15 percentage points less likely to be enrolled in school (Table A2, column 2). The father's absence is significantly correlated with child labor, increasing the probability of the child engaging in overall child labor by 27 percentage points (Table A2, column 4). This suggests that, in the father's absence, the child is left to assume additional responsibilities both inside and outside the home. With the father migrating the child is 25 percentage points more likely to work within the household (column 6) and 6 percentage points more likely to work outside the home (column 8). Hence, with the father gone, the child is less likely to be enrolled in school simply because either he/she is working more or because of the lack of monitoring of the child with the father gone abroad.

Overall, children tend to benefit from remittances since it helps increase school enrollment and reduces overall child labor for the child. However, the physical absence of the father leaves the child worse off. The positive impact of remittances is to an extent offset by the negative effect of the absence of the father, diminishing the net impact of migration for the child.

7.2. LPM Results of Main Specification With Gender Interactions

This specification aims to determine whether the impact of remittances and the father's absence differs between girls and boys (see Tables A3 and A4). For this, the gender terms *male* and *female* interact with both *remittances* and *father absent*. Looking solely at the (*remittances* * *male*) and (*remittances* * fe*male*) terms in Table A4 indicates that remittances benefit both boys' and girls' schooling. However, the magnitude is greater for boys as compared to girls. Remittances increases the probability of being enrolled in school by 25 percentage points for boys as compared to 18 percentage points for girls (column 2). That is, parents are more likely to use the additional money from remittances to send their sons – rather than their daughters – to school. Column (4) of Table A4 show that remittances reduce overall child labor significantly for boys as compared to girls. A boy is 30 percentage points less likely to work. It seems as if for the boys, remittances help them substitute away from child labor and towards schooling as opposed to girls. One possible explanation for this may be that boys are considered the household's future breadwinners: any money spent on their schooling (as opposed to putting them to work) is assumed to increase the future returns on their education. Moreover, in rural households, parents are far more likely to live with their adult sons than their daughters. Most girls in rural Punjab marry after a certain age and move away; parents may accord less value to investing in their schooling if they perceive smaller future returns. These results contradict the moral hazard problem presented by Milligan and Bohara (2007), who suggest that the money coming in through remittances may increase child labor if households decide to start a new business in which their children, particularly boys, are expected to take part. Parents appear to value education and tend to invest in it when they have the money to do so, particularly for the boys.

The father's absence appears to have a negative impact on schooling for girls as compared to the boys, based on the negative coefficient *father absent * female* in column (2) of Table A4. A female child is 14 percentage points less likely to be enrolled in school if her father has migrated abroad, while father's migration has an insignificant impact on boys schooling.

The term *father absent * female* with respect to household child labor is positive and significant, indicating that the father's absence is likely to increase girls 'overall workload, particularly in with the household. Females are 37 percentage points more likely to work due to the absence of their father (column 4). However, where nonhousehold child labor is concerned, the father's absence appears to increase the likelihood of both genders working outside the home, especially boys. Overall, however, the results indicate that remittances are spent more favorably for boys as compared to girls. Remittances help the boys substitute away from child labor towards schooling. While remittances do also increase schooling for girls, they do not significantly lead to a reduction in child labor for the them. As far as child labor is concerned, girls are compelled to work more, as opposed to boys whose burden of work increases only with respect to labor outside the home. Hence, the girls are left with additional household chores and overall work load once the father is away.

7.3. LPM Results of Main Specification With Mother Present Interaction

This specification divides the effect of parental presence into two parts: (i) the father's absence and (ii) the interaction between the father's absence and mother's presence to determine how far the latter offsets the impact of the former (see Tables A5 and A6). Looking at the key variables of interest in Table A6, *remittances* and *father absent*, the results are in line with those in Table A2, i.e., remittances benefit the child while the father's absence leaves the child worse off.

The interaction of the *father absent* variable with *mother present*, i.e., *mother present * father absent*, shows that the mother's presence compensates for the father's absence in households in which the father has migrated. In the second-stage results in Table A6, the variable *father absent* has a negative sign in column (2); its interaction with *mother present* changes the sign to positive for schooling. This suggests that, to some extent, the lack of monitoring on the absent father's part is offset by the mother's role in ensuring that the child concentrates on school.

Even if the father's migration increases the child's household responsibilities, the mother is likely to share in the overall workload. Thus, her role as the primary parental figure responsible for looking after the child on a daily basis and assuming some of the father's household responsibilities in his absence will benefit the child. While the father's absence increases the probability of overall child labor by about 59 percentage points in column (4), the presence of the mother reduces this probability by 65 percentage points. To a greater extent, her presence may even more than offset the rise in child labor.

According to columns (6) and (8), if the father of the child is away but the mother is present at home, a child is 86 percentage points less likely to work at home and 13 percentage points less likely to work outside the household as compared to a child whose parents are both absent.

The idea of "unavailable mothers" – who may be unable to give their children enough time in view of the increased workload they must bear in their spouse's absence – does not seem to hold in rural Punjab. The presence of extended family members, such as older siblings and grandparents, means there are also other adults in the household who are liable to assume part of the workload. In many cases in rural Pakistan, this extends to neighbors – women who share their additional workload with each other, giving them more time to spend with their children.

Another explanation for this result is that, as the mother's responsibility for her children and household increases in the father's absence, so too may her level of empowerment, especially if she is the one receiving the remittances. She may then engage in intra-household bargaining with other family members to protect her children's interests. This redistribution of power enables the mother to determine intra-household allocations. Her concern for her children's wellbeing may lead her to spend more on education and reduce the burden of child labor (Antman, 2012). Moreover, to some extent, the mother's presence is likely to compensate for the father's absence at a psychological level, alleviating the child's loneliness.

Hence, the negative impact of the absence of the father is in large part being offset if the mother is present at home. The mother does not only share the workload, reducing child labor, but also has a positive impact on the child's schooling.

8. Conclusion

This study decomposes the impact of migration into two components: the effect of remittances and the effect of the migrant father's absence on children left behind. While most other studies have looked at one or other of these effects, this study examines both countervailing channels affecting child labor and schooling. It deals explicitly with the issue of endogeneity with respect to remittances and the father's absence by using kinship networks as an IV along with HFE and RE.

The study concludes that remittances enhance children's wellbeing by increasing their likelihood of being enrolled in school rather than engaging in child labor. On the other hand, the migrant father's absence is likely to increase the overall household and nonhousehold workload, part of which may fall to the child at the expense of his/her schooling. The financial benefit of remittances from migration may not completely offset the effect of the father's absence in this context. Given this, we introduce the effect of the mother's presence, assuming she is likely to shoulder the additional workload in the father's absence, monitor the child's schooling and provide the emotional support needed to redress the disruption associated with the father's migration. This greatly reduces the negative effect of the father's absence while we still retain the positive effect of remittances along with the mother's presence.

A gender difference emerges when we look at how the money received through remittances is spent: remittances increases the probability of a boy being enrolled in school by 25 percentage points, while the father's absence compels girls to spend more time working at home, increasing their probability of working at home by about 37 percent. However, to a lesser extent, the father's absence increases the nonhousehold workload for both boys and girls.

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Appendix

Table A1: First-stage results of main specification

	RE		HFE	
	Remittances	**Father absent**	**Remittances**	**Father absent**
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Remittances biraderi IV	0.966***	-0.103*	0.969***	-0.110*
	(0.039)	(0.051)	(0.039)	(0.051)
Migrant biraderi IV	-0.018	1.008***	-0.013	1.005***
	(0.031)	(0.040)	(0.030)	(0.039)
Child's age	0.031	0.019	0.031	0.019
	(0.031)	(0.015)	(0.032)	(0.015)
Child's age sq.	-0.001*	-0.001	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Child's gender	0.009	-0.016	0.003	-0.019
	(0.011)	(0.015)	(0.011)	(0.015)
Father's education	0.005	0.007*	0.002	0.006
	(0.003)	(0.003)	(0.003)	(0.003)
Mother present	-0.074	-0.076	-0.071*	-0.073
	(0.076)	(0.071)	(0.066)	(0.071)
Mother's education	0.002	0.000	0.002	0.000
	(0.006)	(0.008)	(0.006)	(0.008)
HH head's education	0.005**	0.006**		
	(0.003)	(0.002)		

	RE		HFE	
	Remittances	**Father absent**	**Remittances**	**Father absent**
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Wealth	0.009**	0.008*		
	(0.003)	(0.004)		
Size of HH	-0.012	-0.003		
	(0.014)	(0.005)		
Constant	0.031	0.019	0.031	0.019
	(0.031)	(0.015)	(0.032)	(0.015)
District dummies	Yes	Yes	No	No
First-stage F-value of excluded instruments	102.3	120.46	134.8	162.7

Note: RE = random effects, HFE = household fixed effects. Number of observations = 2,963, number of groups = 829. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's calculations.

Table A2: Second-stage results of main specification

	Schooling		Overall child labor		Household child labor		Nonhousehold child labor	
	RE	**HFE**	**RE**	**HFE**	**RE**	**HFE**	**RE**	**HFE**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Remittance	0.168*	0.204**	-0.290***	-0.218*	-0.238**	-0.163	-0.052	-0.073
	(0.079)	(0.095)	(0.083)	(0.100)	(0.082)	(0.097)	(0.035)	(0.047)
Father absent	-0.071	-0.151**	0.223***	0.273***	0.206***	0.249***	0.028	0.060*
	(0.056)	(0.066)	(0.059)	(0.069)	(0.058)	(0.068)	(0.025)	(0.033)
Child's age	0.186***	0.180***	-0.107***	-0.105***	-0.111***	-0.107***	0.006	0.003
	(0.019)	(0.020)	(0.019)	(0.021)	(0.019)	(0.020)	(0.009)	(0.010)
Child's age sq.	-0.010***	-0.009***	0.003***	0.003**	0.004***	0.003**	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Child's gender	-0.008	0.013	0.042*	0.065**	0.050**	0.072***	-0.020*	-0.016
	(0.019)	(0.020)	(0.020)	(0.021)	(0.019)	(0.020)	(0.009)	(0.010)
Father's education	0.001	0.005	-0.002	0.006	0.004	0.014	-0.008***	-0.012***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.016)	(0.002)	(0.003)
Mother present	0.403***	0.356***	-0.251***	-0.294***	-0.276***	-0.324***	0.029	0.035
	(0.032)	(0.038)	(0.034)	(0.040)	(0.033)	(0.039)	(0.014)	(0.019)
Mother's education	0.002	0.006	0.014	0.011	0.024	0.021	-0.019***	-0.021***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.005)	(0.005)
HH head's education	0.002		0.002		0.002		-0.001	
	(0.003)		(0.003)		(0.003)		(0.001)	
Wealth	0.041***		-0.008		-0.008		-0.004	
	(0.006)		(0.007)		(0.007)		(0.003)	
Size of HH	0.020		0.050***		0.056***		-0.003	
	(0.018)		(0.008)		(0.008)		(0.003)	

	Schooling		Overall child labor		Household child labor		Nonhousehold child labor	
	RE	**HFE**	**RE**	**HFE**	**RE**	**HFE**	**RE**	**HFE**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	-0.071	-0.151**	0.223***	0.273***	0.206***	0.249***	0.028	0.060*
	(0.056)	(0.066)	(0.059)	(0.069)	(0.058)	(0.068)	(0.025)	(0.033)
District dummies	Yes	No	Yes	No	Yes	No	Yes	No
Hausman Test P-Value	0.0132		0.0221		0.0288		0.0319	

Note: RE = random effects, HFE = household fixed effects. Number of observations = 2,963, number of groups = 820. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrumented variables = *remittances* and *father absent*.
Source: Author's calculations.

Table A3: First-stage results of main specification with gender interaction

	Random effects				Household fixed effects			
	Remittances * male	Remittances * female	Father absent * male	Father absent * female	Remittances * male	Remittances * female	Father absent * male	Father absent * female
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Remittances biraderi IV * male	0.929***	0.003	0.012	-0.164**	0.930***	0.004	-0.013	-0.006
	(0.042)	(0.026)	(0.038)	(0.052)	(0.042)	(0.026)	(0.052)	(0.071)
Remittances biraderi IV * female	-0.005	1.006***	-0.007	-0.005	-0.004	1.007***	0.007	-0.165**
	(0.057)	(0.036)	(0.052)	(0.071)	(0.057)	(0.036)	(0.038)	(0.052)
Migrant biraderi IV * male	-0.007	-0.016	1.019***	-0.002	-0.001	-0.014	1.003***	0.001
	(0.042)	(0.027)	(0.038)	(0.053)	(0.042)	(0.026)	(0.038)	(0.052)
Migrant biraderi IV * female	-0.003	-0.007	-0.022	1.009***	0.000	-0.007	-0.011	1.004***
	(0.033)	(0.021)	(0.030)	(0.041)	(0.033)	(0.021)	(0.029)	(0.041)
Child's age	0.029**	0.002	0.004	0.015	0.030**	0.002	0.003	0.016
	(0.010)	(0.006)	(0.009)	(0.012)	(0.010)	(0.006)	(0.009)	(0.012)
Child's age sq.	-0.001*	-0.000	-0.000	-0.001	-0.001*	-0.000	-0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Child's gender	0.007	-0.006	-0.019	0.005	0.002	-0.008	-0.020	0.002
	(0.014)	(0.009)	(0.012)	(0.017)	(0.014)	(0.009)	(0.012)	(0.017)
Father's education	0.003	0.002	0.002	0.005	0.000	0.002	0.002	0.003
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
Mother present	-0.052***	-0.022*	-0.031*	-0.044*	-0.049***	-0.021*	-0.032*	-0.041*
	(0.014)	(0.009)	(0.013)	(0.017)	(0.014)	(0.009)	(0.013)	(0.017)
	0.004	-0.002	-0.000	0.000	0.004	-0.002	-0.000	0.000

	Random effects				Household fixed effects			
	Remittances * male	**Remittances * female**	**Father absent * male**	**Father absent * female**	**Remittances * male**	**Remittances * female**	**Father absent * male**	**Father absent * female**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Mother's education	(0.005)	(0.003)	(0.005)	(0.006)	(0.005)	(0.003)	(0.005)	(0.006)
HH head's education	0.004***	0.001	0.001	0.005***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Wealth	0.007**	0.003	0.004	0.004				
	(0.002)	(0.002)	(0.002)	(0.003)				
Size of HH	-0.009**	-0.004	0.002	-0.005				
	(0.003)	(0.002)	(0.003)	(0.004)				
Constant	-0.136**	0.009	-0.007	-0.089	-0.004	1.047***	0.007	-0.165**
	(0.047)	(0.030)	(0.042)	(0.058)	(0.057)	(0.036)	(0.038)	(0.052)
District dummies	Yes	Yes	Yes	Yes	No	No	No	No
First-stage F-value of excluded instruments	87.8	119.9	157.1	119.1	110.3	155.1	203.5	152.7

Note: Number of observations = 2,963, number of groups = 820. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.**Source**: Author's calculations.

Table A4: Second-stage results of main specification with gender interaction

	Schooling		Overall child labor		Household child labor		Nonhousehold child labor	
	RE	HFE	RE	HFE	RE	HFE	RE	HFE
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Remittances * male	0.157*	0.249*	-0.383***	-0.297**	-0.335***	-0.252**	-0.070	-0.085
	(0.094)	(0.127)	(0.098)	(0.115)	(0.097)	(0.112)	(0.042)	(0.054)
Remittances * female	0.202*	0.182*	-0.134	-0.105	-0.084	-0.042	-0.005	-0.035
	(0.114)	(0.109)	(0.119)	(0.134)	(0.117)	(0.131)	(0.053)	(0.063)
Father absent * male	-0.041	-0.160	0.095	0.080	0.041	0.016	0.067	0.105*
	(0.087)	(0.097)	(0.091)	(0.102)	(0.089)	(0.100)	(0.040)	(0.048)
Father absent * female	-0.084	-0.144*	0.294***	0.366***	0.293***	0.361***	0.013	0.037*
	(0.065)	(0.075)	(0.068)	(0.079)	(0.067)	(0.077)	(0.030)	(0.019)
Child's age	0.187***	0.180***	-0.106***	-0.105***	-0.110***	-0.107***	0.007	0.004
	(0.019)	(0.020)	(0.020)	(0.021)	(0.019)	(0.020)		(0.010)
Child's age sq.	-0.010***	-0.009***	0.003***	0.003**	0.003***	0.003**	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.001)
Child's gender	-0.022	0.010	0.064*	0.116***	0.084**	0.136***	-0.039**	-0.037*
	(0.027)	(0.029)	(0.028)	(0.031)	(0.027)	(0.030)	(0.013)	(0.014)
Father's education	0.002	0.005	-0.004	0.003	0.001	0.010	-0.008***	-0.012***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.002)	(0.003)
Mother present	0.402***	0.358***	-0.249***	-0.292***	-0.274***	-0.322***	0.029	0.037
	(0.032)	(0.038)	(0.034)	(0.040)	(0.033)	(0.039)	(0.014)	(0.019)
Mother's education	0.002	0.006	0.015	0.011	0.024*	0.020	-0.018***	-0.021***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.005)	(0.005)
Wealth	0.039***		-0.007		-0.007		-0.004	
	(0.006)		(0.007)		(0.007)		(0.003)	

	Schooling		Overall child labor		Household child labor		Nonhousehold child labor	
	RE	**HFE**	**RE**	**HFE**	**RE**	**HFE**	**RE**	**HFE**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
HH head's education	0.002		0.002		0.002		-0.000	
	(0.003)		(0.003)		(0.003)		(0.001)	
Size of HH	0.020*		0.050***		0.055***		-0.003	
	(0.094)		(0.098)		(0.112)		(0.042)	
Constant	0.202*	0.249*	-0.134	-0.105	-0.084	-0.042	-0.005	-0.035
District dummies	Yes	No	Yes	No	Yes	No	Yes	No
Hausman Test								
P-Value	0.0488		0.0414		0.0340		0.0421	

Note: RE = random effects, HFE = household fixed effects. Number of observations = 2,963, number of groups = 820. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrumented variables = *remittances* * *male*, *remittances* * *female*, *father absent* * *male*, *father absent* * *female*.

Source: Author's calculations.

Table A5: First-stage results of main specification with mother present interaction

	Random effects			Household fixed effects		
	Remittances	Father absent	Mother present * father absent	Remittances	Father absent	Mother present * father absent
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Remittances biraderi IV	0.961***	-0.115*	0.064***	0.959***	-0.131**	0.068***
	(0.039)	(0.048)	(0.017)	(0.039)	(0.048)	(0.017)
Migrant biraderi IV	-0.067*	0.946***	-0.046***	-0.057	0.974***	-0.054**
	(0.031)	(0.038)	(0.013)	(0.030)	(0.037)	(0.013)
Mother present * migrant biraderi IV	0.113***	0.260***	0.996***	0.113***	0.256***	0.997***
	(0.010)	(0.012)	(0.004)	(0.010)	(0.012)	(0.004)
Child's age	0.018	-0.011	0.003	0.018	-0.011	0.004
	(0.011)	(0.014)	(0.005)	(0.011)	(0.014)	(0.005)
Child's age sq.	-0.001	0.000	-0.000	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Child's gender	0.012	-0.009	-0.006	0.008	-0.008	-0.007
	(0.011)	(0.014)	(0.005)	(0.011)	(0.014)	(0.005)
Mother present	0.127**	0.006	-0.164**	-0.130**	-0.208**	-0.162**
	(0.015)	(0.004)	(0.007)	(0.017)	(0.021)	(0.017)
Mother's education	0.003	0.004	-0.002	0.003	0.004	-0.002
	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)	(0.003)
Father's education	0.005	0.006	0.006***	0.002	0.006*	0.005***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
Size of HH	-0.008*	-0.213**	-0.004*			

	Random effects			Household fixed effects		
	Remittances	**Father absent**	**Mother present * father absent**	**Remittances**	**Father absent**	**Mother present * father absent**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	(0.003)	(0.021)	(0.002)			
HH head's education	0.006***	0.007***	0.001			
	(0.001)	(0.002)	(0.001)			
Wealth	0.008**	0.006	-0.001			
	(0.003)	(0.004)	(0.001)			
Constant	-0.067*	0.946***	-0.046***	-0.057	0.974***	-0.054***
	(0.031)	(0.038)	(0.013)	(0.030)	(0.037)	(0.013)
District dummies	Yes	Yes	Yes	No	No	No
First-stage F-value of excluded instruments	109.6	168.0	42.3	140.8	218.7	104.7

Note: Number of observations = 2,963, number of groups = 820. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's calculations.

Table A6: Second-stage results of main specification with mother present interaction

	Schooling		Child labor		Household child labor		Nonhousehold child labor	
	RE	**HFE**	**RE**	**HFE**	**RE**	**HFE**	**RE**	**HFE**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Remittance	0.165*	0.204**	-0.198***	-0.213***	-0.164***	-0.159**	-0.038	-0.072
	(0.079)	(0.095)	(0.036)	(0.043)	(0.043)	(0.053)	(0.034)	(0.045)
Father absent	-0.084	-0.165**	0.577***	0.594***	0.537***	0.540***	0.068*	0.105**
	(0.060)	(0.070)	(0.027)	(0.032)	(0.033)	(0.039)	(0.027)	(0.033)
Mother present * father absent	0.032	0.044*	-0.656***	-0.653***	-0.879***	-0.862***	-0.106***	-0.133***
	(0.023)	(0.025)	(0.011)	(0.012)	(0.013)	(0.014)	(0.011)	(0.012)
Child's age	0.183***	0.175***	-0.011	-0.015	-0.023*	-0.025*	0.016	0.015
	(0.019)	(0.020)	(0.009)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)
Child's age sq.	-0.009***	-0.009***	0.000	0.000	0.001	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Child's gender	-0.007	0.015	0.022*	0.026**	0.033**	0.037***	-0.022*	-0.021*
	(0.019)	(0.020)	(0.009)	(0.009)	(0.010)	(0.011)	(0.009)	(0.010)
Mother present	0.389***	0.338***	-0.134***	-0.008*	-0.538***	0.032	-0.019	-0.423***
	(0.034)	(0.040)	(0.017)	(0.003)	(0.093)	(0.022)	(0.043)	(0.099)
Mother's education	0.002	0.006	0.002	0.001	0.013	0.011	-0.020***	-0.022***
	(0.010)	(0.010)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Father's education	0.001	0.005	0.006*	0.008**	0.010**	-0.015**	-0.008***	-0.012***

	Schooling		Child labor		Household child labor		Nonhousehold child labor	
	RE	HFE	RE	HFE	RE	HFE	RE	HFE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.005)	(0.006)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Wealth	0.040***		0.002		0.002		-0.003	
	(0.006)		(0.003)		(0.003)		(0.003)	
HH size	0.002		0.008*		0.014**		0.100***	
	(0.003)		(0.004)		(0.004)		(0.018)	
HH head's education	0.021**		-0.002		-0.002		-0.001	
	(0.008)		(0.001)		(0.002)		(0.001)	
Constant	0.073***	0.090***	0.933***	0.967***	0.971***	1.011***	0.071***	-0.035
	(0.019)	(0.019)	(0.042)	(0.045)	(0.052)	(0.056)	(0.015)	(0.047)
District dummies	Yes	No	Yes	No	Yes	No	Yes	No
Hausman Test								
P-Value	0.0305		0.0411		0.0501		0.0469	

Note: RE = random effects, HFE = household fixed effects. Number of observations = 2,963, number of groups = 820. Standard errors clustered at district level (seven districts). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrumented variables = *remittances*, *father absent*, *father absent * mother present*.
Source: Author's calculations.

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Globalization, Endogenous Oil Price Shocks and Chinese Economic Activity

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Abstract

Using a structural vector autoregressive model, this study investigates the extent to which international oil price shocks have influenced the Chinese economy over the period 1991–2014. Given China's intensified macroeconomic activity and its increasing demand for energy resources, we also examine the endogenous response of international oil prices to economic conditions in the country. To that end, we derive and empirically estimate a small open-economy New Keynesian model for China and the rest of the world. Our results show that the Chinese economy is relatively more sensitive to global economic conditions than to domestic policy actions. Global productivity shocks appear to be the most important variable causing Chinese macroeconomic activity through trade, where oil prices impact aggregate demand negatively.

Keywords: Globalization, macroeconomic fluctuations, oil price shocks, SVAR, China.

JEL classification: C32, E32, F41, Q43.

1. Introduction

Identifying the underlying causes and effects of an oil price shock is key to understanding its transmission mechanism and potential aftermath for oil-importing economies. It can also help in formulating an appropriate policy to counter the resulting economic instability.

It is widely held that recent global oil market developments have resulted from faster economic growth in developing economies such as China, India and Turkey. China is the world's most populous country, with a population of 1.3 billion. As the second largest economy, it has grown on

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average by 10 percent per annum in the last two decades and more than 500 million people have been lifted out of poverty. China is also among the world's most open trading economies. Its energy demand has risen proportionally to cater to the needs of its growing manufacturing sector: since 1993, China has shifted from being an oil exporter to an oil importer. In 2013, it became the world largest energy consumer and the second largest importer of oil after the US.

Given these features, China is often cited as one of the world's most important economic players. Arguably, its considerable demand for oil may cause high energy prices and consequently have an adverse impact on oil-importing economies through various channels. That said, China's economic growth helps promote growth in other economies through its high demand for imports and cheaper exports. Similarly, with the global economic boom, the demand for Chinese manufacturing goods has increased, in turn promoting growth in China. Thus, the interconnectedness of the Chinese economy and the rest of the world seem to be two sides of the same coin.

This study's objective is to investigate the comparative effects of global demand shocks on the Chinese economy, along with the resulting oil price shocks. It also examines oil price dynamics and the relative strength of different sources. Section 2 provides a comprehensive survey of the literature. Section 3 outlines the macroeconomic performance of the Chinese economy. Our theoretical model, derived from a New Keynesian framework, is presented in Section 4 and the estimation and identification procedure is explained in Section 5. Finally, the study's empirical evidence and concluding remarks are given in Sections 6 and 7.

2. Literature Survey

Since 1973, numerous studies have examined the nexus between oil price shocks and macroeconomic performance in developed economies. Hamilton's (1983) pioneering study establishes a robust causal negative relationship between international oil price movements and the US GNP for the period 1948–72. After the oil market collapsed in the 1980s and oil prices fell significantly, many observers expected an economic revival – or at least recovery – to follow. That this did not happen prompted many economists to re-examine the oil price-macroeconomy relationship.

Using extended data for the period during which oil prices fell, Mork (1989) reconsiders Hamilton's (1983) study and finds that the oil price-macroeconomy relationship is asymmetric when oil prices increase but not when they decrease. Bernanke, Gertler and Watson (1997) study the role of endogenous monetary policy responses to oil price shocks and observe that the recession of the 1970s could have been avoided had the policy response been more accommodating. Studies such as Ferderer (1996) and Hooker (1996) gauge the role of uncertainty and the prevailing environment in the impact of oil price shocks.

Several recent empirical studies have discovered, however, that the oil price-macroeconomy relationship has weakened since the 1980s (see Hooker, 1999). The observed increased resilience of the global economy to oil price shocks remains a puzzle: among the different explanations for this are more flexible markets, more credible monetary policy and the smaller share of oil in production (Blanchard & Galí, 2009; Blanchard & Riggi, 2011). However, this argument is not plausible because it disregards the endogenous response of oil prices to global economic activity (see Woodford, 2007; Hamilton, 2009; Kilian, 2009).

As Kilian (2009) argues, oil price shocks stem from different sources and these have different implications for output and inflation, making it important to identify the causal source of the oil price shock. He classifies oil price shocks as being supply-driven (stemming from geopolitical events), demand-driven (due to improved global productivity), related to the precautionary demand for oil (resulting from geopolitical uncertainties) and related to specific oil market shocks. In the demand-driven case, given a stagnant oil supply, the increased demand for oil will push up its nominal price. Consequently, oil-importing countries will be burdened as they will have to pay more for the same quantity of oil. On the other hand, they will enjoy cheaper imports (other than oil) from more productive countries. Demand for their exports will also rise due to the productivity shock to the rest of the world.

In China's case, only limited efforts have been made to examine the oil price-macroeconomy relationship. Huang and Guo (2007) study the behavior of the Chinese real effective exchange rate (REER) in response to oil price shocks. They find that positive oil price shocks lead to a smaller currency appreciation in China relative to its trading partners, which they attribute to its smaller share of oil in production. Cong et al. (2008) demonstrate that most of China's stock market indices do not respond significantly to oil price fluctuations.

Faria et al. (2009) focus on China's export performance and find significant positive associations between oil prices and exports. Ou, Zhang and Wang (2012) show that the West Texas Intermediate crude oil price has had a significant effect on various domestic price indicators such as the consumer price index (CPI) and producer price index for China, although this relationship appears to have weakened up to 2011. Similarly, Wang and Zhang (2014) examine the asymmetric response of industrial production to oil price shocks and find that a fall in the oil price has a stronger positive impact on industrial production than decreases in industrial production due to an oil price increase.

At the aggregate level, Du, He and Wei (2010) and Tang, Wu and Zhang (2010) find that oil price shocks significantly affect China's macroeconomic performance. Looking at the role of expected and unexpected oil price volatility, Zhang and Chen (2014) show that oil price volatility has a bearing on the country's aggregate commodity market. In contrast, Chen, Chen and Wu's (2009) empirical study of the impact of China's economic growth on international oil prices rejects the argument that China is the main culprit behind the current oil price hike. Finally, Wu and Zhang (2014) revisit the role of Chinese crude oil imports in world oil price volatility for the period 2005–13. Their results do not support the hypothesis that China's crude oil imports cause Brent crude oil prices in the short run as well as long run.

Given the context described above, this study contributes to the literature by deriving and estimating an open-economy dynamic stochastic general equilibrium model for the Chinese economy.

3. The Chinese Economy: Some Stylized Facts

Prior to economic reforms introduced in 1979, the Chinese economy was centrally planned, poor and relatively isolated from the global economy. Post-reforms, it became one of the world's foremost emerging economies, registering an annual growth rate of almost 10 percent in the last two decades. More recently, China has emerged as the world's fastest growing economy and is currently the second largest economy after the US. Since 2000, China has been a popular destination for foreign direct investment (FDI). Annual FDI inflows to China stood at US$121 billion in 2013 and the total stock of FDI was an estimated US$832.9 billion through 2012 (United Nations Conference on Trade and Development, 2014). This inflow of financial resources has been accompanied by modern technology and information, enhancing China's productivity and driving its rapid economic growth. Moreover, the country's supply of cheap labor enables it to produce in bulk, making it the world's largest manufacturer.

China's trade sector has been its second most important source of growth since the early 1990s. In 2012, it became the world's largest trading economy, overtaking the US. Over the last two decades, Chinese exports have grown by 18.5 percent and imports by 17.3 percent, creating a large trade surplus. Between 2004 and 2013, the trade surplus rose sharply from US$32 billion to US$261 billion. In 2013, Chinese exports constituted 12.1 percent of the world's merchandised exports, compared to 2.1 percent in 1991. China's economic growth has also relied heavily on coal and oil: in 2009, it was the world's largest energy consumer, followed by the US. Coal accounts for the bulk of China's energy mix, constituting about 69 percent, followed by oil at 18 percent, although China is still the world's second largest oil consumer after the US. The country has significant oil reserves and was a net oil exporter until 1992. Since 1993, it has been a net oil importer, importing 5.8 million barrels per day in 2013.

These characteristics of the Chinese economy show why it is important to study the potential impact of China's growing energy demand on global energy prices. We also look at the impact of rising energy prices on global demand and inflation and the impact of global macroeconomic dynamics on China as a secondary effect.

4. Theoretical Model

Our theoretical model of the Chinese economy is an extension of Galí and Monacelli's (2005) model of a small, open economy within a New Keynesian framework. The rationale for adopting this model is China's imperfect market structure (centrally planned), which a New Keynesian framework can accommodate. The model is extended in several directions, with oil as a factor of production and imperfect financial markets that generate a risk premium. The macroeconomic variables of the rest of the world are assumed to be endogenous, along with oil prices. Other assumptions regarding preferences, the structure of the goods market and the state of technology remain constant.

4.1. Household

The domestic economy consists of n consumers, each of whom seek to maximize their lifetime utility:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) \quad (1)$$

where N_t denotes the work effort in hours and C_t is a composite consumption index comprising domestically produced goods $C_{H,t} = \left[\int_0^1 C_{H,t}(j)^{(\varsigma-1)/\varsigma} dj\right]^{\frac{\varsigma}{\varsigma-1}}$ and goods imported from the rest of the world $C_{F,t} = \left[\int_0^1 {C_{k,t}}^{(\tau-1)/\tau} di\right]^{\frac{\tau}{\tau-1}}$. ς is the elasticity of substitution between goods produced domestically in any country and τ is the elasticity of substitution between domestic and imported goods. $C_{k,t}$ is the index of goods imported from the kth country, σ is the degree of relative risk aversion, β is the discount factor and φ is the inverse elasticity of labor supply. The aggregate consumption index can be expressed as

$$C_t = \left[(1-\alpha)^{\frac{1}{\tau}} C_{H,t}^{(\tau-1)/\tau} + \alpha^{\frac{1}{\tau}} C_{F,t}^{(\tau-1)/\tau}\right]^{\tau-1/\tau} \tag{2}$$

where α is the share of imported goods in the domestic consumer's basket and can be considered the degree of openness of the trading economy. The domestic CPI (P_t) is the weighted sum of the domestic price index $P_{H,t} = \left[\int_0^1 P_{H,t}(j)^{1-\varsigma} dj\right]^{\frac{1}{1-\varsigma}}$ and imported price index $P_{F,t} = \left[\int_0^1 {P_{i,t}}^{1-\tau} di\right]^{\frac{1}{1-\tau}}$ where $P_{i,t} = \left[\int_0^1 P_{i,t}(j)^{1-\varsigma} dj\right]^{\frac{1}{1-\varsigma}}$. The domestic CPI can be written as

$$P_t = \left[(1-\alpha)P_{H,t}^{1-\tau} + \alpha P_{F,t}^{1-\tau}\right]^{1/(1-\tau)} \tag{3}$$

The domestic consumer's utility maximization is subject to a lifetime budget constraint given by[1]

$$P_t C_t + E_t\{ℸ_{t,t+1} D_{t+1}\} \le D_t + W_t N_t + T_t \tag{4}$$

where $ℸ_{t,t+1}$ is the stochastic discount factor and D_t is the nominal payoff received by the household in period t for the portfolio held in period t – 1. W_t is the nominal wage rate and T_t denotes nominal transfer payments.

The optimization process yields the following optimality conditions:

$$w_t - p_t = \sigma c_t + \varphi n_t \tag{5}$$

$$c_t = -\frac{1}{\sigma}(i_t - E_t\{\pi_{t+1}\} - \rho) + E_t\{c_{t+1}\} \tag{6}$$

[1] For a detailed derivation, see Galí and Monacelli (2005).

where equation (5) is the household's labor supply decision and equation (6) represents the intertemporal substitution behavior in consumption. The lowercase letters are the logs of the respective variables and $E_t\{\pi_{t+1}\}$ is the expected price inflation in period $t + 1$. Finally, i is the nominal rate of interest and $\rho = -\log \beta$.

4.2. Financial Markets

Financial markets are integrated with the rest of the world. The bilateral real exchange rate is the ratio of the domestic country's CPI to the rest of the world's CPI expressed in the domestic country's currency $Q_t = \frac{E_{k,t}P_t^k}{P_t}$.

Further, we assume that the law of one price holds for each good across small open economies. Thus, the relationship between the domestic country's CPI, domestic inflation and the REER around the symmetric steady state can be expressed as

$$p_t = p_{H,t} + \frac{\alpha}{1-\alpha} q_t \quad (7)$$

$$\pi_t = \pi_{H,t} + \frac{\alpha}{1-\alpha} \Delta q_{t+1} \quad (7a)$$

Since asset markets are assumed to be complete, with identical household preferences across the world, this implies there is a symmetric optimization problem. The rest of the world is assumed to be large enough for the small open economy to have no influence over it. Combining the Euler equations for both economies, we obtain the risk-sharing condition, which links domestic consumption to the rest of the world's consumption instead of domestic income:

$$c_t = c_t^* + \frac{1}{\sigma} q_t \quad (8)$$

Another important implication of complete asset markets is the uncovered interest parity (UIP) condition, which implies that exchange rate movements depend solely on the real interest rate differential:

$$E_t\{\Delta q_{t+1}\} = (r_t - E_t\{\pi_{t+1}\}) - (r_t^* - E_t\{\pi_{t+1}^*\}) \quad (9)$$

Equations (8) and (9) imply that financial market integration ensures consumption smoothing at a macro-level and that any economy can minimize idiosyncratic risk by trading with the international community.

Since there is weak empirical evidence to suggest that the UIP condition holds in the short run (see, among others, Mark & Wu, 1998; Hansen & Hodrick, 1980), we incorporate a risk premium for the relationship to hold:

$$E_t\{\Delta q_{t+1}\} = (r_t - E_t\{\pi_{t+1}\}) - (r_t^* - E_t\{\pi_{t+1}^*\}) + \varepsilon_t^q \quad (10)$$

where ε_t^q is the time-varying risk premium incorporating a transitory deviation from the UIP condition.

4.3. Supply Side

Firms are assumed to be identical with respect to the production process (technology). We also assume that they function in a monopolistic environment and produce differentiated products. Each firm tries to maximize its profit subject to demand conditions and its price-setting ability. It produces with constant-returns-to-scale technology, defined by a Cobb-Douglas production function as shown below.

$$Y_t(j) = [A_t N_t(j)]^\eta O_t^d(j)^{1-\eta} \quad (11)$$

where O_t^d is the demand for oil by each firm, A_t is labor productivity, η is the share of labor in the production process and $1-\eta$ is the share of oil. The firm's cost minimization condition implies that its marginal products are equal:

$$(1-\eta)W_t N_t(j) = \eta O_t^d(j) P_{O,t} \quad (12)$$

where $P_{O,t}$ is the price of oil. The demand for oil by any firm is given by

$$o_t^d = \left[\frac{\eta\sigma+1+\varphi}{1+\varphi(1-\eta)}\right] y_t - \left[\frac{\eta(1+\varphi)}{1+\varphi(1-\eta)}\right] a_t - \left[\frac{\eta}{1+\varphi(1-\eta)}\right] p_{O,t} \quad (13)$$

Using the cost minimization condition, the log real marginal cost function of the domestic firm can be written as

$$mc_t = \eta w_t + (1-\eta)p_{O,t} - \eta a_t - p_{H,t} \quad (14)$$

Assuming prices are sticky in the goods market, the price-setting mechanism is assumed to follow Calvo's (1983) structure, where a random fraction Ω of firms cannot adjust their prices optimally. Thus, Ω is the firm's inability to adjust its prices in period t and measures price rigidity. The optimal price setting, subject to the firm's demand schedule, yields a traditional Phillips curve:

$$\pi_{H,t} = \beta E_t\{\pi_{H,t+1}\} + \lambda\widehat{mc}_t \quad (15)$$

where $\lambda = \frac{(1-\theta)(1-\beta\theta)}{\theta}$ and $\widehat{mc}_t$ is the deviation of the real marginal cost from its flexible price equilibrium.

4.4. Demand-Side Equilibrium

$$Y_t(j) = C_{H,t}(j) + \int_0^1 C_{H,t}^i(j)di \quad (16)$$

where $Y_t(j)$ is the total production of commodity j, $C_{H,t}(j)$ is the total final consumption expenditure of the domestic household and $\int_0^1 C_{H,t}^i(j)di$ denotes total exports to the rest of the world. Using the optimal allocation condition of resources for a small open economy and the rest of the world, and given the real exchange rate definition and identical preferences, the symmetric steady-state aggregate demand function can be written as

$$y_t = c_t + \tau(p_t - p_{H,t}) + \alpha\left(\tau - \frac{1}{\sigma}\right)q_t \quad (17)$$

Using equation (7a), the risk-sharing condition and Euler condition, we obtain a dynamic IS equation:

$$y_t = E_t\{y_{t+1}\} - \frac{1}{\sigma}(i_t - E_t\{\pi_{t+1}\}) - \alpha\left[\frac{1+(2-\alpha)(\tau\sigma-1)}{\sigma(1-\alpha)}\right]E_t\{\Delta q_{t+1}\} \quad (18)$$

4.5. Supply-Side Equilibrium

This section establishes the relationship between real marginal cost and economic activity and derives the New Keynesian Phillips curve. After substituting equations (5) and (7), equation (14) can be rewritten as

$$mc_t = -\eta a_t + \eta(\sigma c_t + \varphi n_t) + (1-\eta)\tilde{p}_{O,t} + \frac{\alpha}{1-\alpha}q_t \quad (19)$$

where $\tilde{p}_{O,t}$ is the real price of oil. Now, inserting the cost minimization condition (12), production function (11) and risk-sharing condition (8) into the above equation, we obtain

$$mc_t = -\xi_1 a_t + \xi_2 y_t^* + \xi_3 y_t + \xi_4\tilde{p}_{O,t} + \xi_5 q_t \quad (20)$$

where $\xi_1 = \frac{\eta(1+\varphi)}{1+\varphi(1-\eta)}$, $\xi_2 = \frac{\eta\sigma}{1+\varphi(1-\eta)}$, $\xi_3 = \frac{\eta\varphi}{1+\varphi(1-\eta)}$, $\xi_4 = \frac{(1+\varphi)(1-\eta)}{1+\varphi(1-\eta)}$, $\xi_5 = \frac{\eta}{1+\varphi(1-\eta)} + \frac{\alpha}{1-\alpha}$ and $\xi_6 = \frac{\sigma}{\alpha\gamma\sigma(2-\alpha)+(1-\alpha)^2}$.

Inserting equation (20) into the Phillips curve (15) and incorporating a cost-push shock, such as in Clarida, Galí and Gertler (2002), yields

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda\xi_8 x_t + \lambda\xi_9 q_t + \lambda\xi_{10}\tilde{p}_{o,t} + \varepsilon_t^{\pi} \tag{21}$$

Using the definition of the output gap and the AR(1) productivity process, and assuming that government spending is exogenously determined, the New Keynesian IS equation derived is

$$x_t = E_t\{x_{t+1}\} - \frac{1}{\sigma}(i_t - E_t\{\pi_{t+1}\}) - \alpha\left[\frac{1+(2-\alpha)(\tau\sigma-1)}{\sigma(1-\alpha)}\right]E_t\{\Delta q_{t+1}\} - \frac{(\xi_2-\xi_6)}{(\xi_3+\xi_6)}E_t\{\Delta y_{t+1}^*\} - \frac{\xi_4}{(\xi_3+\xi_6)}E_t\{\pi_{O,t+1}^*\} + \varepsilon_t^a \tag{22}$$

where ε_t^a is the shock to domestic productivity. We assume that monetary policy is conducted according to the forward-looking Taylor rule:

$$i_t = \phi_\pi E_t\{\pi_{t+1} - \pi^T\} + \phi_x x_t + \varepsilon_t^i \tag{23}$$

where π^T is the target inflation rate and ε_t^i denotes the interest rate shock. The rest of the world's economy evolves in a closed economy framework, with no influence from the small open economy. Other assumptions concerning preferences, technology and market structure remain constant, such that the structural equations describing the rest of the world are:

$$x_t^* = E_t\{x_{t+1}^*\} - \Pi_1(r_t^* - E_t\{\pi_{t+1}^*\}) - \Pi_2 E_t\{\pi_{O,t+1}^*\} - \Pi_3(1 - \rho_{a^*})a_t^* + \varepsilon_t^{a^*} \tag{24}$$

$$\pi_t^* = \beta E_t\{\pi_{t+1}^*\} + \lambda\Pi_4 x_t^* + \lambda\Pi_5\tilde{p}_{O,t}^* + \varepsilon_t^{\pi*} \tag{25}$$

$$i_t^* = \phi_\pi^*\pi_t^* + \varepsilon_t^{i*} \tag{26}$$

4.6. Oil Market Equilibrium

We assume that the oil supply is exogenously determined and follows an AR(1) process, as given in Backus and Crucini (2000):

$$o_t^{s*} = \rho_O o_{t-1}^{s*} + \varrho_t \tag{27}$$

Firms operating in the rest of the world are assumed to influence the world oil price. Their demand for oil is given by

$$o_t^{d*} = \left[\frac{\eta\sigma+1+\varphi}{1+\varphi(1-\eta)}\right]y_t^* - \left[\frac{\eta(1+\varphi)}{1+\varphi(1-\eta)}\right]a_t^* - \left[\frac{\eta}{1+\varphi(1-\eta)}\right]\tilde{p}_{O,t}^* \tag{28}$$

Thus, the equilibrium price in the international market can be obtained through the market clearing condition:

$$\tilde{p}^{*}_{0,t} = \Lambda_1 y^{*}_t - \Lambda_2 a^{*}_t - \Lambda_3 o^{s*}_t + \varepsilon^{po}_t \quad (29)$$

where $\Lambda_1 = \sigma + \frac{(1+\varphi)}{\eta}$, $\Lambda_2 = 1 + \varphi$ and $\Lambda_3 = \frac{1+\varphi(1-\eta)}{\eta}$.

5. Methodology

The rational expectations hypothesis assumes that rational and future-oriented economic agents give more weight to expected movements in economic variables than to observed times series. This implies that they update their information set consistently and revise their expectations. Given this, modern macroeconomists have devised micro-foundational models in which the economic agent's decisions stem from intertemporal optimization problems. The core model is estimated using Keating's (1990, 2000) two-step procedure. For a clear exposition of the methodology for estimating a system of equations using the full information maximum likelihood method, see Leu (2011) and Nawaz and Ahmed (2015).

5.1. Identification Problem

The system of structural equations representing the open economy and the rest of the world (Keating, 1990; Leu, 2011) derived in the previous section can be written as:

$$x_t = \alpha_0 + E_t\{x_{t+1}\} - \alpha_1(i_t - E_t\{\pi_{t+1}\}) - \alpha_2 E_t\{\tilde{\pi}_{o,t+1}\} - \alpha_3 E_t\{\Delta q_{t+1}\} - \alpha_4 E_t\{x^{*}_{t+1}\} + \varepsilon^{a}_t \quad (5.1)$$

$$\pi_t = \beta_0 + \beta_1 E_t\{\pi_{t+1}\} + \beta_2 x_t + \beta_3 \tilde{p}_{o,t} + \beta_4 q_t + \varepsilon^{\pi}_t \quad (5.2)$$

$$q_t = \gamma_0 + E_t\{q_{t+1}\} - \gamma_1(i_t - E_t\{\pi_{t+1}\}) + (i^{*}_t - E_t\{\pi^{*}_{t+1}\}) + \varepsilon^{q}_t \quad (5.3)$$

$$i_t = \phi_0 + \phi_\pi E_t\{\pi_{t+1}\} + \phi_x x_t + \varepsilon^{i}_t \quad (5.4)$$

$$x^{*}_t = \alpha^{*}_0 + E_t\{x^{*}_{t+1}\} - \alpha^{*}_1(r^{*}_t - E_t\{\pi^{*}_{t+1}\}) - \alpha^{*}_2 E_t\{\tilde{\pi}^{*}_{0,t+1}\} + \varepsilon^{fa*}_t \quad (5.5)$$

$$\pi^{*}_t = \beta^{*}_0 + \beta^{*}_1 E_t\{\pi^{*}_{t+1}\} + \beta^{*}_2 x^{*}_t + \beta^{*}_3 \tilde{p}_{o,t} + \varepsilon^{\pi*}_t \quad (5.6)$$

$$i^{*}_t = \phi^{*}_0 + \phi^{*}_\pi \pi^{*}_t + \varepsilon^{i*}_t \quad (5.7)$$

$$p_{o,t} = \rho_o + \rho_1 x^{*}_t + \varepsilon^{op}_t \quad (5.8)$$

To incorporate short-run dynamics and the revision of expectations in a structural vector autoregressive (VAR) framework, we need to convert the system of structural equations described by (5.1) to (5.8) into structural shocks and VAR innovation representations as given below.

$$\varepsilon_t^{fa} = e_t^x - E_t\{x_{t+1}\} + \alpha_1\big(e_t^i - (E_t\{\pi_{t+1}\} - E_{t-1}\{\pi_{t+1}\})\big) + \alpha_2\{(E_t\{\widetilde{P}_{o,t+1}\} - E_{t-1}\{\widetilde{P}_{o,t+1}\}) - e_t^{op}\} + \alpha_3(E_t\{q_{t+1}\} - E_{t-1}\{q_{t+1}\}) - e_t^q + \alpha_4(E_t\{x_{t+1}^*\} - E_{t-1}\{x_{t+1}^*\}) - e_t^{x*} \quad (5.1a)$$

$$\varepsilon_t^{\pi} = e_t^{\pi} - \beta_1(E_t\{\pi_{t+1}\} - E_{t-1}\{\pi_{t+1}\}) - \beta_2 e_t^x - \beta_3 e_t^{op} - \beta_4 e_t^q \quad (5.2a)$$

$$\varepsilon_t^q = e_t^q - (E_t\{q_{t+1}\} - E_{t-1}\{q_{t+1}\}) + \gamma_1\big(e_t^i - (E_t\{\pi_{t+1}\} - E_{t-1}\{\pi_{t+1}\})\big) - (e_t^{i*} - (E_t\{\pi_{t+1}^*\} - E_{t-1}\{\pi_{t+1}^*\})) \quad (5.3a)$$

$$\varepsilon_t^i = e_t^i - \phi_\pi(E_t\{\pi_{t+1}\} - E_{t-1}\{\pi_{t+1}\}) - \phi_x e_t^x \quad (5.4a)$$

$$\varepsilon_t^{fa*} = e_t^{x*} - (E_t\{x_{t+1}^*\} - E_{t-1}\{x_{t+1}^*\}) + \alpha_1^*\big(e_t^{i*} - (E_t\{\pi_{t+1}^*\} - E_{t-1}\{\pi_{t+1}^*\})\big) + \alpha_2^*(E_t\{\widetilde{P}_{o,t+1}\} - E_{t-1}\{\widetilde{P}_{o,t+1}\}) \quad (5.5a)$$

$$\varepsilon_t^{\pi*} = e_t^{\pi*} - \beta_1^*(E_t\{\pi_{t+1}^*\} - E_{t-1}\{\pi_{t+1}^*\}) - \beta_2^* e_t^{x*} - \beta_3^* e_t^{op} \quad (5.6a)$$

$$\varepsilon_t^{i*} = e_t^{i*} - \phi_\pi^* e_t^{\pi*} \quad (5.7a)$$

$$\varepsilon_t^{op} = e_t^{op} - \rho_1 e_t^{x*} \quad (5.8a)$$

where $e_t^y = y_t - E_{t-1}y_t$ is the VAR innovation for each endogenous variable and $E_t\{y_{t+1}\} - E_{t-1}\{y_{t+1}\}$ denotes the process by which rational economic agents revise their expectations. To estimate the terms involved in updating future expectations – of the domestic output gap, the real price of oil, domestic inflation, the REER, global demand and global inflation $(x_t, \pi_t, q_t, p_{o,t}, x_t^*, \pi_t^*)$ – the unrestricted stacked VAR form can be written as

$$Y_t = AY_{t-1} + Qe_t \quad (5.9)$$

Assuming the system follows an AR(1) process, then by the same approach,

$$E_t Y_{t+1} = AY_t \quad (5.10)$$

Since we have six variables with a forward-looking component, we generate the following vector to locate each endogenous variable:

$$\acute{r}_y = (1, 0, 0, 0, 0, 0 \ldots\ 0) \text{ for the first endogenous variable} \tag{5.11}$$

The location will change for the next variable to be located and so on. Thus, the expected value of any endogenous variable one period ahead can be achieved by multiplying (5.10) by the vector we constructed in (5.11), such that

$$E_t Y_{t+1} = \acute{r}_y A Y_t$$

The expectations revision process as defined above is the difference between the observed value and its expected value in period $t - 1$. Thus,

$$E_t Y_{t+1} - E_{t-1} Y_{t+1} = \acute{r}_y A Y_t - \acute{r}_y A E_{t-1} Y_t$$

$$= \acute{r}_y A (Y_t - E_{t-1} Y_t) \tag{5.12}$$

Using (5.9), we obtain

$$= \acute{r}_y A Q e_t \tag{5.13}$$

Inserting the final solution into the system of structural equations (5.1a) to (5.8a) expressed in VAR innovations yields:

$$\varepsilon_t^a = e_t^x - (\acute{r}_x A Q e_t) + \alpha_1 \left(e_t^i - (\acute{r}_\pi A Q e_t)\right) + \alpha_2 \{(\acute{r}_{op} A Q e_t) - e_t^{op}\} + \alpha_3 (\acute{r}_q A Q e_t) - e_t^q + \alpha_4 (\acute{r}_{x*} A Q e_t) - e_t^{x*} \tag{5.14}$$

$$\varepsilon_t^\pi = e_t^\pi - \beta_1 (\acute{r}_\pi A Q e_t) - \beta_2 e_t^x - \beta_3 e_t^{op} - \beta_4 e_t^q \tag{5.15}$$

$$\varepsilon_t^q = e_t^q - (\acute{r}_q A Q e_t) + \gamma_1 \left(e_t^i - (\acute{r}_\pi A Q e_t)\right) - (e_t^{i*} - (\acute{r}_{\pi*} A Q e_t)) \tag{5.16}$$

$$\varepsilon_t^i = e_t^i - \phi_\pi (\acute{r}_\pi A Q e_t) - \phi_x e_t^x \tag{5.17}$$

$$\varepsilon_t^{fa*} = e_t^{x*} - (\acute{r}_{x*} A Q e_t) + \alpha_1^* \left(e_t^{i*} - (\acute{r}_{\pi*} A Q e_t)\right) + \alpha_2^* (\acute{r}_{op} A Q e_t) \tag{5.18}$$

$$\varepsilon_t^{\pi*} = e_t^{\pi*} - \beta_1^* (\acute{r}_{\pi*} A Q e_t) - \beta_2^* e_t^{x*} - \beta_3^* e_t^{op} \tag{5.19}$$

$$\varepsilon_t^{i*} = e_t^{i*} - \phi_\pi^* e_t^{\pi*} \tag{5.20}$$

$$\varepsilon_t^{op} = e_t^{op} - \rho_1 e_t^{x*} \tag{5.21}$$

5.2. Estimation Under Rational Expectation Restrictions

The matrix form of the dynamic structural model of the open economy can be written as

$$\mathfrak{Z}_0 y_t = \mathfrak{Z}_1 y_t + \cdots \mathfrak{Z}_q y_{t-q} + \mathcal{D}_0 z_t + \cdots + \mathcal{D}_k z_{t-k} + \varepsilon_t \,, \varepsilon_t \sim (0, Z) \quad (5.22)$$

where $y_t = (x_t, \pi_t, q_t, i_t, x_t^*, \pi_t^*, i_t^*, p_{o,t})$ is a vector of domestic and foreign endogenous variables and $z_t = (a_t, s_t, a_t^*)$ is a vector of exogenous variables. $\mathfrak{Z}$ and $\mathcal{D}$ are coefficient matrices for the endogenous and exogenous variables with different lags of order q and k. The term $\varepsilon_t = (\varepsilon_t^{fa}, \varepsilon_t^{\pi}, \varepsilon_t^{q}, \varepsilon_t^{i}, \varepsilon_t^{fa*}, \varepsilon_t^{\pi*}, \varepsilon_t^{i*}, \varepsilon_t^{op})$ includes structural shocks. The reduced-form VAR is obtained by multiplying the dynamic structural model by $\mathfrak{Z}_0^{-1}$ as follows:

$$y_t = \mathcal{V}_1 y_{t-1} + \cdots \mathcal{V}_q y_{t-q} + F_1 z_{t-1} + \cdots + F_k z_{t-k} + e_t \,, \varepsilon_t \sim (0, Z) \quad (5.23)$$

where $\mathcal{V}_i = \mathfrak{Z}_0^{-1}\mathfrak{Z}_i$, $F_i = \mathfrak{Z}_0^{-1}\mathcal{D}_i$ and $e_t = \mathfrak{Z}_0^{-1}\varepsilon_t$.

6. Empirical Results

The estimation has two steps. We start by estimating the reduced-form VAR and obtaining parameter coefficients in combination with the rational expectation restrictions imposed on $\mathfrak{Z}_0$. The exclusion restrictions located on the contemporaneous exogenous variables are in $\mathcal{D}_0$. Next, assuming structural disturbances are i.i.d. and normally distributed, we estimate the system using the maximum likelihood method. A comprehensive analysis is carried out by computing the impulse response functions (IRFs) and variance decomposition.

6.1. Data and Diagnostic Assessment

The model is estimated using quarterly data for the period 1991Q1 to 2013Q4, with a total of 92 observations. It comprises 11 variables – eight endogenous and three exogenous. To adjust for seasonal variation, three dummies are introduced, along with a constant term. The domestic endogenous variables include the output gap, inflation rate, REER and interest rate. The endogenous variables representing the rest of the world include the output gap (world GDP), inflation rate (US), interest rate (Federal funds rate) and nominal price of oil (Dubai, Fateh). Productivity and oil supply (million barrels per day) are exogenous variables. The output gap is computed by applying the Hodrick-Prescott filter to time series data for China's real GDP. Productivity is computed as the log difference between GDP and the labor force. The other variables are constructed as theoretical measures, as stated in the model. The data series for the variables (except oil supply) were obtained from the International Financial Statistics database. The oil supply data was obtained from the International Energy Agency database.

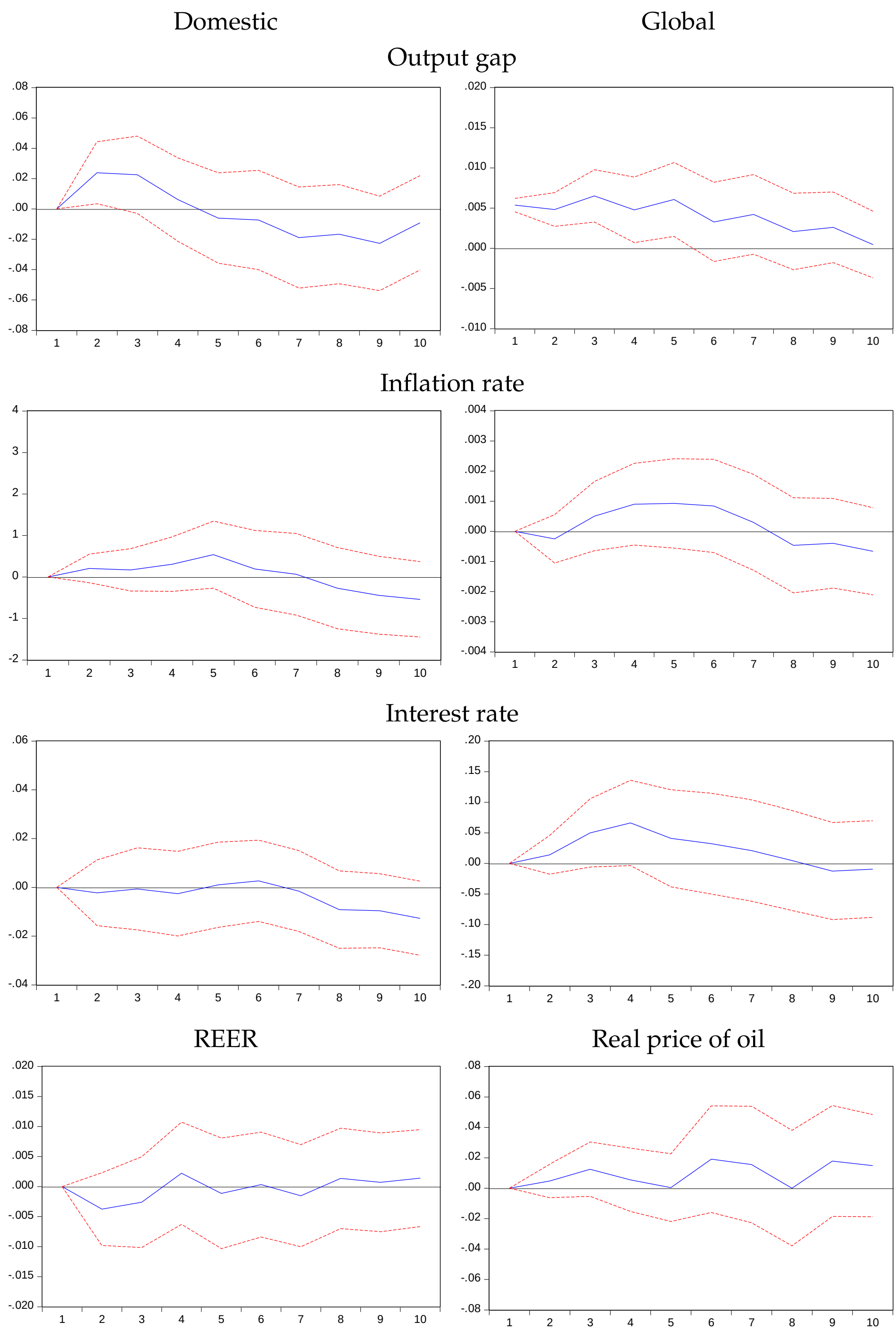
We use the augmented Dickey-Fuller test to check the nonstationarity of the data at level and first-order difference without intercept. The lag order is determined using the Akaike information criterion. The result confirms the existence of a unit root at level, but the data appears to be stationary when first-order differenced. An asymmetric VAR approach is adopted to achieve greater flexibility in dynamic specifications. Different lag lengths are specified for the endogenous and exogenous variables. Prior to estimation, we use various diagnostic tests to ensure the statistical adequacy of the reduced-form VAR model (results not reported here). We find no evidence of serial correlation or heteroskedasticity and the VAR residuals are normally distributed. Overall, the residual diagnostic tests support the statistical adequacy of the reduced-form VAR structure.

6.2. Global Demand Shock

We test the extent to which recent global economic conditions – characterized by a global economic boom and energy price hike – can explain variations in China's output growth, inflation rate, REER and interest rate. The dynamic response of the target variables is estimated through IRFs and variance decomposition. Given the scope and length of this article, the discussion is confined to the relative impact of an endogenous oil price shock in the presence of a global economic boom and the impact of an increase in global demand for goods and services.

Our results for the impact of a global demand shock are largely consistent with the literature (see Blanchard & Galí, 2009; Kilian, 2009; Campolmi, 2008) and confirm that China's economic performance depends considerably on global economic conditions (see Figure 1). The domestic output gap responds appreciably to a global demand shock. A positive shock to global demand promptly increases the domestic output gap; the impact persists for a year, peaking in the first quarter. However, in the long run, the output gap remains below the steady-state level for the next six quarters.

Figure 1: IRFs for a one-standard deviation shock to global output



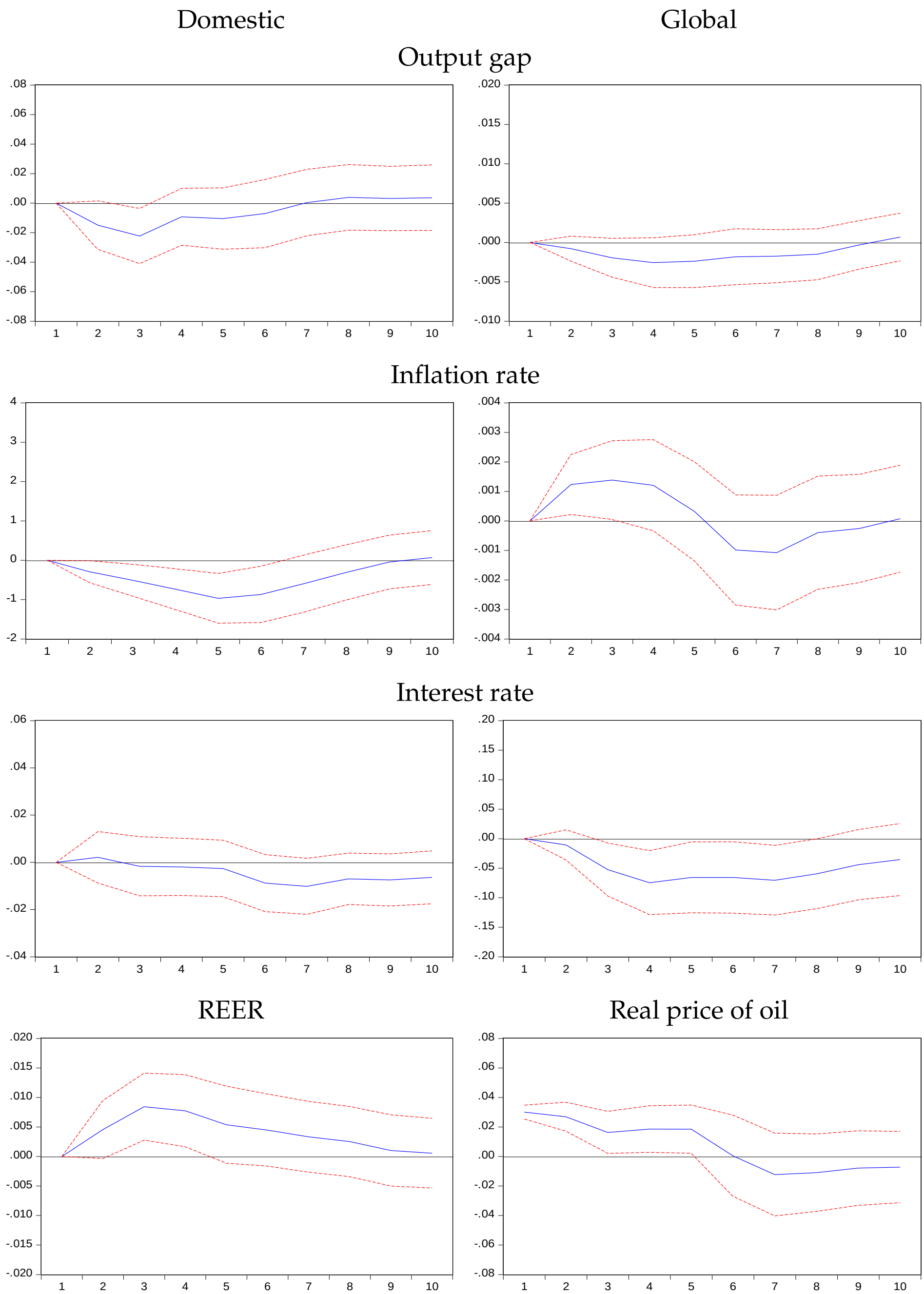
Domestic price inflation remains relatively unaffected or is slightly higher than the steady-state level in the fifth and sixth quarters. The REER depreciates significantly and takes four quarters to adjust. The monetary authority responds with an accommodative policy taking into account the general price stability. However, if we look at the rest of the world's macroeconomic dynamics, substantial price inflation is evident, which persists for about eight quarters after the global economy experienced the demand shock. The monetary authorities in the rest of the world are more concerned about economic stability (inflation) and respond aggressively with higher interest rates.

The most striking result is the positive relationship between the global demand shock and the price of oil. The real price of oil rises as the demand for other goods increases, but never dips below the steady-state value. The oil price movement is cyclical, but stays above its steady-state level. Each cycle takes four to five quarters to complete. Overall, the analysis implies that global demand shocks have a positive impact on the Chinese economy. These results are in line with Sun and Heshmati (2010) and Fan (2008) who find that the international trade volume and structure favor Chinese exports and stimulate economic growth in the country.

6.3. Oil Price Shock

Given the potentially positive impact of global demand on Chinese exports during the last two decades and the country's financial integration with the rest of the world, we incorporate the impact of an endogenous oil price increase on the Chinese economy (Figure 2). As discussed above, global demand shocks have had a strong impact on China's output growth, with China becoming the world's second largest economy and second largest importer of oil after the US in 2010.

Figure 2: IRFs for a one-standard deviation shock to the price of oil



We find a substantial drop in China's output gap, which persists for about seven quarters after an oil price increase. The output gap falls promptly, reaching its lowest level in the third quarter, and then starts to recover in the fourth quarter. The global output gap also declines due to the positive oil price shock, which strengthens the latter's distortionary consequences. However, we find no signs of price inflation. A possible explanation for the low inflation rate lies in the economy's greater dependence on coal and other domestic energy resources. The REER depreciates significantly after an oil price hike episode and takes ten quarters to readjust. As there is no (or low) inflation, the monetary authority does not respond in the short run. However, it introduces an expansionary monetary policy, given the observed deflationary trends.

Tang et al. (2010) report comparable results for the Chinese economy. Although their analysis emphasizes the long-run consequences in a closed economy setup, they explain the output drop with a declining capacity utilization ratio in the short run as the effect of oil prices – the principal channel – hits the economy. In an open-economy framework, however, we cannot confirm the supply-side effect, even in the short run.

Unlike the supply-side channel, the demand-side channel seems to play a crucial role in domestic output. China is an export-oriented economy and its past high economic growth stems (in addition to FDI) mainly from outstanding growth in exports. However, the global demand for goods and services declines immediately following the oil price shock. Here, the decline in global demand is caused by the demand-side channel as well as supply-side channel. The demand-side channel works through a discretionary income effect, operating cost effect, uncertainty effect and an increase in precautionary saving. The supply-side channel affects firm production via higher marginal costs (Edelstein & Kilian, 2007, 2009). The lower global demand and supply spiral puts downward pressure on the demand for Chinese exports. FDI also declines as firms in the rest of the world operate below capacity and make less or no profit in addition to low private savings.

6.4. Variance Decomposition Analysis

The forecast error variance decomposition (FEVD) analysis demonstrates that external global factors, including world inflation, world demand and oil price shocks (which represent global economic activity), have a strong impact on China's economic activity. The world demand shock is the leading source of variation, accounting for 55 percent of the variation in domestic output in the short run, followed by the global cost-push shock, which explains about 37 percent of the fluctuations in domestic output. The endogenous oil price shock is the third source of the domestic output gap: it explains 6 percent of the demand forecast variance error, which declines slowly over five years. Domestic shocks generated by fiscal policy, the cost push, risk premium and interest rate have a negligible impact on China's domestic output gap (Table 1).

Table 1: FEVD analysis for output gap

Period	SE	Fiscal policy shock	Cost push shock	Risk premium shock	Interest rate shock	Global demand shock	Global cost push shock	Global interest rate shock	Oil price shock
1	22.80585	0.143617	0.008240	0.060592	0.031687	55.40576	37.59282	0.455745	6.301538
2	25.51746	0.144563	0.007702	0.055633	0.067025	56.83081	37.31439	0.364967	5.214913
3	27.91307	0.172733	0.007233	0.048466	0.137789	57.57746	37.02728	0.305252	4.723793
4	33.85119	0.127795	0.007204	0.035871	0.148288	56.75001	37.79668	0.300382	4.833780
8	40.59025	0.142892	0.007361	0.054769	0.131788	57.94582	37.11797	0.289850	4.309558
12	52.86315	0.150100	0.007579	0.067994	0.110581	58.22773	36.50305	0.270286	4.662679
16	53.46388	0.148110	0.007493	0.068538	0.109330	58.34027	36.46577	0.265667	4.594820
20	53.86733	0.152262	0.007481	0.068901	0.117362	58.30811	36.50614	0.268983	4.570759

The inflation rate dynamics are different (Table 2). In the first quarter, the oil price shock explains about 36.47 percent of the variation in domestic inflation, but this declines steadily in the second quarter and is the least important source of domestic inflation fluctuations in the long run. The global demand shock is found to be the most important source of inflation rate variability. It accounts for 41 percent of the variation in domestic inflation in the first quarter, rising steadily and explaining about 61 percent of the inflation forecast variance error. The shock to global inflation is the second most important source of variation. In the first quarter, it explains 17 percent of the variation; this increases in the long run, capturing 36 percent of the variation.

Table 2: FEVD analysis for inflation rate

Period	SE	Fiscal policy shock	Cost push shock	Risk premium shock	Interest rate shock	Global demand shock	Global cost push shock	Global interest rate shock	Oil Price shock
1	5.899661	1.191599	3.149161	0.075396	0.079679	41.73740	17.16211	0.137822	36.46684
2	10.44080	9.571692	1.010259	0.283663	4.542782	30.48568	35.68626	0.885170	17.53450
3	311.6898	0.010740	0.006587	0.062212	0.015611	60.04360	36.33626	0.131760	3.393224
4	590.4548	0.003467	0.005217	0.053404	0.019212	59.64439	36.65766	0.131801	3.484851
8	881.5349	0.011018	0.003556	0.054390	0.019284	59.06980	36.61908	0.189969	4.032903
12	1420.756	0.027700	0.004165	0.076714	0.013843	61.29224	36.01531	0.138051	2.431981
16	1685.301	0.023465	0.004617	0.072318	0.014077	61.44541	35.93802	0.118248	2.383844
20	1720.684	0.024938	0.004640	0.070488	0.020250	61.38697	35.98049	0.115927	2.396293

The REER and interest rate variations (Tables 3 and 4) depend primarily on global factors rather than domestic macroeconomic variables. The variation in these variables can be explained by the global demand shock, inflation rate dynamics and oil prices. These three sources jointly explain 99 percent of the variation in the REER as well as interest rate in the short run. Given China's high degree of openness, these variables may also influence the economy in the longer run. The only exception is the domestic interest rate: domestic variables account for about 7 percent of the variation in the first quarter. The inability of the domestic central bank to control inflation and the interest rate is evident here and could probably be attributed to the economy's high degree of openness and large FDI inflows.

Table 3: FEVD analysis for REER

Period	SE	Fiscal policy shock	Cost push shock	Risk premium shock	Interest rate shock	Global demand shock	Global cost push shock	Global interest rate shock	Oil price shock
1	6.481647	0.002892	0.016133	0.010024	0.114417	55.48864	37.82077	0.201804	6.345325
2	6.947161	0.082979	0.015105	0.008728	0.258944	55.98468	37.29965	0.186612	6.163299
3	6.975591	0.164335	0.016096	0.008688	0.323463	55.97884	37.02822	0.295394	6.184963
4	7.054316	0.259661	0.017646	0.011122	0.384990	55.42695	37.01853	0.404807	6.476295
8	7.548679	0.279289	0.017203	0.028168	0.376604	55.78519	36.61905	0.406921	6.487577
12	12.49115	0.259634	0.011538	0.071002	0.219180	57.12387	36.23716	0.372196	5.705420
16	13.23550	0.259269	0.011558	0.069630	0.207843	56.77222	36.20050	0.378001	6.100982
20	13.28324	0.267869	0.011533	0.070265	0.216298	56.78090	36.12884	0.382837	6.141455

Table 4: FEVD analysis for interest rate

Period	SE	Fiscal policy shock	Cost push shock	Risk premium shock	Interest rate shock	Global demand shock	Global cost push shock	Global interest rate shock	Oil price shock
1	4.264646	3.157346	0.009424	0.540077	4.002030	62.11363	25.54066	0.205107	4.431732
2	8.386646	1.202949	0.011249	0.250966	1.380082	60.02498	32.88594	0.352549	3.891282
3	8.403721	1.252972	0.011267	0.267538	1.516278	59.80576	32.80828	0.357395	3.980514
4	9.777168	0.930281	0.010232	0.214015	1.121081	58.89171	33.76622	0.333669	4.732787
8	22.01669	0.213607	0.009757	0.081931	0.222118	56.04233	36.25793	0.338182	6.834138
12	25.68963	0.185180	0.008551	0.093393	0.189077	58.03857	35.69487	0.275207	5.515159
16	28.29561	0.168326	0.008620	0.090651	0.158024	58.76087	35.51909	0.238256	5.056167
20	30.31351	0.152791	0.008275	0.089268	0.138328	59.44485	35.25642	0.210241	4.699826

So far, the global inflation rate and increased global demand for goods and services, along with endogenous oil price variations, seem to play a major role in China's macroeconomic dynamics. These three variables account for almost 99 percent of the variation in each domestic variable in the short run as well as in the long run. The overall analysis confirms the ineffectiveness of domestic policy variables in influencing the major macroeconomic variables in a highly open economy.

Global demand shocks are the most important factor explaining the variation in oil prices (Table 5). Aggregate global demand shocks explain 55 percent of the variance in the short run and 61 percent of the forecast error variance in the long run. This is followed by global cost-push shocks, which account for 29 percent of the variation in the second quarter and about 35 percent after five years. The world interest rate accounts for about 2 percent of the variation in the third and fourth quarters only. China's output gap explains only 1 percent of the forecast error variance in the short run.

Table 5: FEVD analysis for oil price

Period	SE	Fiscal policy shock	Cost push shock	Risk premium shock	Interest rate shock	Global demand shock	Global cost push shock	Global interest rate shock	Oil price shock
1	1.000405	0.000000	0.000000	0.000000	0.000000	0.080900	0.000000	0.000000	99.91910
2	3.662825	0.832410	0.010517	0.000069	1.374353	55.41690	29.43203	0.150287	12.78343
3	4.582119	0.993976	0.006930	0.039529	1.219980	53.85571	20.98860	2.008252	20.88702
4	5.711451	0.728963	0.004625	0.077489	0.853351	57.69804	19.91328	1.806790	18.91747
8	30.27477	0.084215	0.010483	0.035346	0.206535	61.31755	34.74978	0.249950	3.346141
12	35.77726	0.080444	0.008718	0.048124	0.157701	61.45984	35.21522	0.238918	2.791033
16	36.53691	0.111318	0.008495	0.052532	0.185759	61.63278	35.01896	0.260360	2.729796
20	37.29742	0.108512	0.008412	0.051676	0.181951	61.48358	35.11068	0.256690	2.798492

7. Conclusion

The study's key findings suggest that global economic conditions have a significant impact on China's economy. Domestic policy variables, including fiscal and monetary policy shocks, appear to have the least influence on the country's macroeconomic dynamics. Global demand shock is the most important variable, with positive implications for domestic GDP and other variables. Collectively, the global demand shock and global cost-push shock (excluding oil price shocks) explain more than 90 percent of the variation in the Chinese economy for any horizon (up to five years in this study). In the case of positive oil price shocks, China's GDP experienced a downward trend that lasted a year and a half. The decline in inflation following an oil price hike can be explained by the substantial decrease in demand for Chinese products due to a slump in the rest of the world. The inflation rate in the rest of the world follows a positive trend due to the high marginal cost of production.

The study's most important finding is the FVED of the international oil price level. Our results confirm the oil price endogeneity hypothesis: oil price variations depend primarily on global economic conditions in the long run. Oil prices start responding to global economic conditions in the second quarter. Global demand shocks play a major role in shaping oil market dynamics and explain up to 61 percent of the variation in oil prices. However, the interest rate appears to cause no variation in oil prices in any horizon.

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Free Trade: Does Myopic Policy Overlook Long-Term Gains?

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Abstract

This article analyzes the correlation between trade liberalization and welfare in Pakistan from 1986 to 2015. Using consumption expenditure as a measure of welfare, we estimate the relationship using a vector error correction model. The empirical results show that trade liberalization does not have an immediate correlation with welfare: it takes some time for liberalization policies to enhance welfare. The findings also suggest that trade liberalization can help reduce poverty, decrease inequality and increase enrollment levels in the long run. But in the short run, trade liberalization has led to higher income inequality.

Keywords: Welfare, trade liberalization, social indicators, Pakistan.

JEL classification: F13.

1. Introduction

Liberalization policies are aimed at achieving global integration through policy choices pertaining to trade and price liberalization, budget restructuring, privatization and social safety nets, among others. Trade liberalization is considered a crucial component of economic integration and has garnered considerable attention in the growth and welfare literature, given that trade policy choices play an important role in determining growth.

Developing countries were generally criticized earlier for adopting import substitution policies. After the formation of the World Trade Organization (WTO), free trade and trade barrier reduction were emphasized. Countries are classified as liberalized economies if (i) their average tariff rate is less than 40 percent, (ii) nontariff barriers cover less than 40 percent of their trade, (iii) the black market exchange rate is not less than 20 percent relative to the official exchange rate, (iv) the state has no monopoly over major exports and (v) the country does not follow a socialist economic system (Sachs & Warner, 1995).

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Proponents of trade liberalization argue that it improves growth, enhances economic efficiency and leads to greater equality, thus making it a win-win strategy. Liberalization leads to stronger competition, increases efficiency by ensuring more efficient resource allocation, and helps achieve economies of scale through access to world markets and productivity gains through the adoption of new technologies (Sachs & Warner, 1995). Open economies are better able to absorb technological advancements generated by scientifically advanced countries, thereby improving their likelihood of growth (Wacziarg & Welch, 2008).

Some postwar developing countries that initiated policies of trade liberalization and subsequently witnessed considerable growth include Cyprus, Hong King, Malaysia, Mauritius, Singapore and Thailand. Their economic transformation has led many economists to focus on the impact of liberalization on growth (see, for instance, Sachs & Warner, 1995; Wacziarg & Welch, 2008; Harrison, 1996; Chatterji, Mohan & Dastidar, 2014). The story that emerges in the literature is that open economies – whether developed or developing – have higher growth rates than closed ones. Their average growth rates also reveal that, among open economies, developing countries have higher growth rates than developed countries (Harrison, 1996; Gries & Redlin, 2012). Other studies document the relationship between trade liberalization and economic growth for Pakistan (see Din, Ghani & Siddique, 2003; Siddiqui & Iqbal, 2005; Yasmin, Jehan & Chaudhary, 2006).

While trade liberalization enhances growth, its impact on welfare needs to be evaluated, given that it is expected to create winners and losers (Winters & Martuscelli, 2014). Various factors determine the impact of trade liberalization policy on economic and social welfare, including which sectors have been liberalized and households' earning sources. Individuals working in the export sector, for instance, will enjoy gains, while those working in import competing sectors may face losses, with policy effects operating through resource reallocation and the displacement of workers (Winters & Martuscelli, 2014; Federici & Montalbano, 2010).

Liberalization policy can have an immediate impact in the form of access to more varieties of goods and services available to both producers and consumers. Its effect also operates through how price changes induced by liberalization affect different income groups (Deaton, 1989; Benjamin & Deaton, 1993; Raihan, 2010). Public spending on welfare may fall, since government revenues generated in the form of tariffs are likely to be affected by liberalization (Ingco, 1997).

The impact of liberalization can also operate through how relative wages are determined in a country. The standard Heckscher–Ohlin model predicts that trade liberalization is advantageous to factor-abundant countries, in this case, developing countries with abundant unskilled labor. Advocates of liberalization support this argument, pointing to the rising skill premium in the US. That said, this argument has been challenged with respect to developing countries (Topalova, 2007). Liberalization may induce capital deepening – which requires skills to complement capital – and support skilled labor instead, resulting in an increase in relative wages. In this sense, liberalization does not necessarily improve income distribution.

In the case of developing countries where product markets tend to be imperfect, protection may lead to rent sharing and liberalization may promote rent dissipation and increase relative wages (Robbins, 2003). In tandem with rising growth and wages due to liberalization, an increase in the returns to education can promote investment in education. In the long run, this would count as a positive impact of liberalization.

With global integration, faster economic growth and poverty reduction require an adjustment period. This can be costly, with poor households often bearing the burden (Banerjee & Newman, 2004). Despite the benefits and losses to some in the short and long run, the advantages of liberalization – in terms of technology diffusion, efficiency of international trade and exchange, and the merits of living in an open society – are thought to outweigh its disadvantages. This warrants further research to identify the role of liberalization in determining the welfare of individuals in a society.

Pakistan initially followed an import substitution policy before moving toward liberalization. After becoming a member of WTO, the country was required to reduce its trade barriers and liberalized its trade in 2001 (Wacziarg & Welch, 2008). This paper examines the relationship between trade liberalization and welfare for Pakistan over the years 1986 to 2015. Given the dearth of studies on the relationship between welfare and trade liberalization, it aims to contribute to the literature by examining the impact of trade liberalization on welfare in Pakistan using consumption as a measure of welfare.

The paper also analyzes the correlation between social indicators and trade liberalization to gauge whether the latter's benefits translate into consumption gains alone or if there are any improvements in education and health as well as declining poverty and inequality. There is no other evidence of this relationship for Pakistan. The study's findings suggest that the benefits of trade liberalization are more pronounced in the long run in terms of improved welfare in the shape of higher enrolment, reductions in poverty and lower inequality, while there is little evidence of these benefits in the short run.

Section 2 outlines Pakistan's trade policy. Sections 3 and 4 present the study's methodology and results. Section 5 concludes.

2. Pakistan's Trade Policy

Initially, Pakistan's trade policy focused on import substitution with the imposition of tariffs, quantitative restrictions, import licensing and nontariff barriers to protect domestic industry from foreign competition. In the 1960s, its trade policy emphasized export promotion through an export bonus scheme and by providing preferential access to foreign exchange. Import liberalization policies were also pursued, which included the renewal of import licenses and reduction in import controls. The economy experienced a large deficit in the balance of trade, which was financed by foreign loans. The export bonus scheme continued into the 1970s, accompanied by the elimination of restrictive licensing and currency devaluation. These policies did not increase exports relative to imports, thus leading to a current account deficit that was financed primarily through external sources.

To increase exports and imports, the government took several steps in the 1980s, including the removal of import quotas on noncapital imports and the liberalization of restricted imports by setting tariff rates for these imports and reducing tariff slabs. The economy continued to experience a current account deficit, albeit a smaller one than in the last decade. The reduction in imports, increase in remittances and foreign assistance received during the Afghan war led to an improvement in the balance of payments. During the 1990s, Pakistan's trade policy moved further toward trade liberalization. Nontariff barriers were removed, all items were allowed as imports, the maximum level of tariff was reduced, and export finance and credit guarantee schemes were launched. The current account deficit worsened the balance of payments, and this was exacerbated by the decline in remittances and foreign aid accompanied by economic sanctions.

Pakistan liberalized its economy in 2001 and continued to pursue a trade liberalization agenda. Export promotion measures included the provision of a freight subsidy of 25 percent for exports of new products. This policy continued till 2005 for leather products. Pakistan also signed different trade agreements, including a preferential trade agreement (PTA) with the ECO countries, the South Asian Free Trade Agreement with the SAARC countries and a PTA with China. Its exports benefited from the GSP Scheme under which Pakistani goods were given duty-free access to EU markets.

Subsequently, the country's trade policy focused on promoting exports through the development of clusters and the establishment of agricultural export processing zones and special export zones. Under this policy, services were considered a major industry with considerable export potential. The 25 percent freight subsidy policy continued and was extended to finished furniture goods. In 2005, as a member of WTO, Pakistan removed all quotas from imports. Second-hand goods were also added to the list of imports allowed. Once sanctions were lifted, foreign aid inflows rose. The country also experienced a large influx of remittances, which improved the balance of payments. The increase in oil prices, however, led to large import bills. Exports increased, primarily in rice, textiles, leather footwear, engineering goods and cement. Imports also rose, largely in textile machinery, agricultural machinery and chemicals.

The 2005/06 Rapid Export Growth Strategy aimed to improve market access for exports and target new markets. Pakistan initiated a free trade agreement (FTA) with Sri Lanka, a PTA with China and bilateral negotiations with Malaysia, Singapore, Indonesia, Turkey, Kazakhstan and other countries, as well as preferential access arrangements with SAARC and the ECO. Under the GSP scheme, all Pakistan's major exports could now enter the EU at concessional tariffs. Import liberalization was also part of this policy: more items were allowed into the country with standards prescribed. Exports increased by 14.14 percent over the previous year, but the increase in the import bill due to rising oil prices widened the trade gap.

In 2006, the Trade Development Authority of Pakistan (TDAP) was established to enhance trade. The 25 percent freight subsidy scheme was extended to goods exported to Africa and Eastern Europe. Customs duties on imported raw material and equipment – such as marble and marble machinery, horticulture and its machinery, raw material for footwear and rice boiling plants – were reduced. The increase in oil prices continued to generate high import bills and the economy experienced an increase in exports, primarily in textiles and in gems and jewelry.

Pakistan's trade policy focused on improving the competitiveness and productivity of exports through the provision of long-term financing. A social, environmental and security compliance board was proposed under the TDAP to ensure export quality standards. The country's import policy continued to emphasize liberalization, allowing industrial units to import machinery under specific regulations and standards as well as second-hand goods and machinery with stated age of use. As imports increased, the current account deficit continued for several reasons: the increase in oil prices, the wheat crisis and resulting wheat imports, the increase in palm oil prices, and the shortage of cotton, leading to cotton imports.

The trade policy of 2008/09 aimed to increase exports in several ways, including export diversification, trade promotion by the TDAP through exhibitions and trade fairs, the development of export clusters, and the establishment of the Federal Export Promotion Board and Trade Dispute Settlement Organization. The government also allowed inputs for exports to be imported at a zero rate of duty. An FTA with China was launched to establish industrial units in China-specific zones in Pakistan. Other key agreements included Pakistan's participation in SAFTA and the Regional Agreement on Trade in Services among the SAARC countries. However, the decline in economic activity in the US and EU led to a fall in Pakistan's exports, especially in textiles. Most recently, the country's trade policy has continued to focus on increasing export competitiveness and diversification with the provision of long-term loans. The policy also emphasizes increasing the number of FTAs with Pakistan's major trading partners. But, even in the presence of these policies, the trade deficit has continued to expand at an alarming rate, with rising imports and stagnant exports.

3. Methodology

This article examines the relationship between trade liberalization and welfare, using data from the World Development Indicators for the period 1986–2015. Welfare is measured by consumption expenditure, which is considered a better measure than income.[1] The welfare model is illustrated below, where welfare measured by consumption is a function of income or output, trade volume and government expenditure:

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[1] Various forms of consumption can be used to measure welfare, including the log of consumption, growth in consumption, consumption equivalent and the difference between expected and observed levels of consumption growth. The debate in the literature pertains to the relative merits of income and consumption as measures of welfare. Consumption offers several advantages at the individual as well as collective level and is considered a more direct measure of wellbeing than income. It is less likely to suffer from underreporting or reporting bias. Measurement problems with income are problematic when one is analyzing changes in the wellbeing of the poor since it may be correlated with government policies in the form of social safety nets. Thus, consumption is also appropriate in cases where people do not earn any form of income and represents a true measure of their welfare. On the other hand, consumption is most likely to be smoothed over a period whereas income may be more fluctuating. Various studies have justified the use of consumption as a measure of welfare, including Jones and Klenow (2010); Topalova (2007); Meyer and Sullivan (2003); Deaton (1989); Federici and Montalbano (2010); Raihan (2010); Pradhan (2009).

$$C = f(Y, T, G) \tag{1}$$

where consumption is represented by *C*, real income by *Y* (measured as real GDP), trade liberalization (exports and imports) by *T* and government expenditure by *G*.

Consumption is measured by household final consumption expenditure, which is the market value of all goods and services (including durables) purchased by the household. Income is measured by GDP at the purchaser's price, which is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Trade liberalization is measured as the sum of exports and imports of goods and services.[2] Government expenditure is general government final consumption expenditure, which includes all government current expenditure on the purchase of goods and services, including employee compensation. All variables used are measured in constant 2010 US dollars and in log form. Figure 1 shows an upward trend in consumption and trade, both of which increased rapidly post-liberalization (post-2000). The empirical analysis will determine if the increase in welfare is attributable to trade.

Figure 1: Trade and final consumption expenditure trends, 1968 to 2012

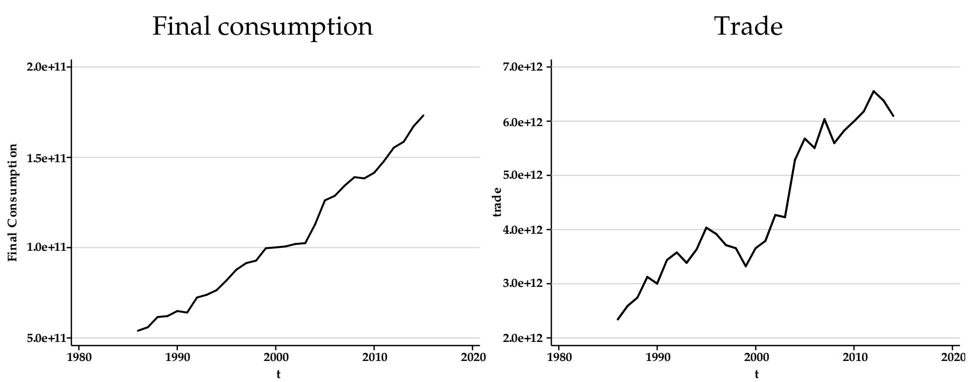

Table 1 gives the summary statistics for consumption and trade before (1986–2000) and after (2001–15) trade liberalization. We see that both

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[2] Various measures can be used to gauge openness or trade liberalization, including exports (or imports) as a percentage of GDP, the ratio of exports plus imports to GDP, a dummy variable for the year in which a country liberalized its trade, the index of trade liberalization and tariffs. We use the sum of exports and imports to measure trade liberalization rather than considering their ratio to GDP since the model already includes income as a separate independent variable. There is an extensive literature to support this choice of variable. See, for instance, Harrison (1996); Frankel and Romer (1996, 1999); Yanikkaya (2003); Burgoon (2001); Bekaert, Harvey and Lundblad (2005).

average consumption and trade have risen over the years, as have their standard deviations from the mean.

Table 1: Summary statistics

Variable	1986–2000	2001–15
Final household consumption		
Average	75,900,000,000	135,000,000,000
Standard deviation	15,600,000,000	23,300,000,000
Trade		
Average	3,230,000,000,000	5,410,000,000,000
Standard deviation	565,000,000,000	963,000,000,000

Source: Author's calculations based on data from the World Development Indicators.

The model specified in equation (1) cannot be estimated using ordinary least squares since the variables at level may be nonstationary. We therefore employ a vector error correction model (VECM)[3] to provide evidence of the long-run relationship between welfare and trade:

$$\Delta C_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1,i} \Delta X_{t-i} + \sum_{i=1}^{k} \alpha_{2,i} \Delta C_{t-i} + \sum_{i=1}^{k} \theta \, ect_{t-i} + \varepsilon_t \quad (2)$$

where C is consumption, X is a vector of all the independent variables specified above (T, G and Y), *ect* is the error correction term, α is the short-run impact of the independent variables, θ is the parameter of the error correction term (*ect*) measuring the error correction mechanism that drives X_t and C_t back to their long-run equilibrium, and i is the number of lags to be included in the VECM specification.

To obtain consistent estimates, we start by determining the presence of a unit root using the augmented Dickey–Fuller (ADF) test. The results in Table 2 show that all the variables are nonstationary at level, but stationary when first-differenced, at which point they are integrated of order one. We apply the Phillips–Perron test (see Table A1 in the Appendix) to check for stationarity and obtain similar results.

[3] The VECM allows for bidirectional causality between all the variables in the model and these variables are dealt with symmetrically in the estimations. We focus on the direction of the relationship running from liberalization to welfare and other social indicators, not the other way around. However, the literature on growth and liberalization does point out that openness measured by imports plus exports is likely to be endogenous. See, for example, Rodriguez and Rodrik (2001); Frankel and Romer (1999); Irwin and Terviö (2002); Winters, McCulloch and McKay (2002).

Table 2: ADF test statistics

Variable	Level t-statistic	First-difference test statistic	Order of integration
ln consumption (C)	-0.831	-6.001***	I(1)
Ln GDP (Y)	-1.408	-3.277**	I(1)
Ln trade (T)	-1.635	-5.739***	I(1)
Ln government expenditure (G)	-0.027	-7.097***	I(1)

Note: If test statistic > critical value, we reject H_o of nonstationarity.
Source: Author's calculations.

Since all the variables are integrated of the same order, there may also be a linear combination between the variables that is stationary. Thus, we need to determine whether the variables are cointegrated. This is done using the Johansen and Juselius multivariate trace and maximal eigenvalue cointegration test. We check for cointegration and determine the rank of the cointegrating vectors, the results of which are presented in Table 3.

Table 3: Cointegration test results for welfare model (Johansen–Juselius maximum likelihood method)

$$C_t = \alpha_o + \alpha_1 T_t + \alpha_2 Y_t + \alpha_3 G_t + \mu_t$$

Null hypothesis	Alternative hypothesis	Cointegration test statistic	1% critical value
$r = 0$	$r > 0$	95.0981	54.64
$r \leq 1$	$r > 1$	45.4542	34.55
$r \leq 2$	$r > 2$	14.0563*	18.17

Source: Author's calculations.

The trace statistics obtained are greater than the critical values for $r = 2$. This implies that the null hypothesis of no cointegration is rejected for the trace tests. The trace statistics test the null hypothesis that the number of cointegrating relationships is r against k cointegrating relationships, where k is the number of endogenous variables. The results suggest that there are at least two cointegrating vectors. Although the series at level is nonstationary, it is integrated of the same order, indicating that there exists a linear combination between the series that is stationary. We conclude that the variables are cointegrated and a VECM can be estimated.

The lags for the VECM are determined using several pre-estimation diagnostic tests: the Akaike information criterion (AIC), the Hannan–

Quinn criterion (HQC) and the Schwarz Bayesian criterion (SBIC). The results for the lag order selection are given in Table 4. According to the AIC, the lag length is 4, while the HQC and SBC yield a lag length of 1.[4] We select the lag length using the AIC.

Table 4: Lag order selection criteria for welfare model

Lags	AIC	HQC	SBC
0	-7.89458	-7.83884	-7.70103
1	-14.46200	-14.18330*	-13.49420*
2	-14.46220	-13.96060	-12.72020
3	-13.96880	-13.24420	-11.45260
4	-14.68590*	-13.73840	-11.39550

Source: Author's calculations.

4. Results

This section presents the results for the relationship between welfare and trade liberalization and between social indicators and trade liberalization.

4.1. Relationship Between Welfare and Trade Liberalization

The results for the VECM using equation (2) are presented in Table 5, which gives the long-run and short-run estimates of welfare in terms of consumption with respect to trade, GDP and government expenditure.

[4] The results are verified by changing the lag length.

Table 5: Welfare VECM short-run and long-run estimates

Variable	**Short run**	**Long run (1st cointegrating equation)**	**Long run (2nd cointegrating equation)**
ΔC_{t-1}	-0.156	1	-5.33e-15
	(0.598)		
ΔC_{t-2}	0.212		
	(0.534)		
ΔC_{t-3}	0.090		
	(0.473)		
ΔY_{t-1}	0.499	-0.773***	
	(0.225)	(0.293)	
ΔY_{t-2}	-0.743		24.639***
	(0.369)		(8.487)
ΔY_{t-3}	-1.350*		
	(0.664)		
ΔT_{t-1}	0.038	0.0749	
	(0.209)	(0.324)	
ΔT_{t-2}	0.297		21.011**
	(0.196)		(9.390)
ΔT_{t-3}	0.270*		
	(0.159)		
ΔG_{t-1}	-0.0182	1.73e-18	1
	(0.145)		
ΔG_{t-2}	-0.006		
	(0.154)		
ΔG_{t-3}	0.063		
	(0.105)		
Constant	0.064**		
	(0.028)		
Error correction term 1	-0.200		
	(0.342)		
Error correction term 2	0.003		
	(0.001)		
R-squared	0.834		
N	26		

Note: Dependent variable = C. Independent variables = Y, T and G. The equation was estimated with four lags of the independent variables and two cointegrating ranks for 1986–2015. All variables are in log form. Standard errors given in parentheses. *** = 1 percent significance level, ** = 5 percent significance level and * = 10 percent significance level.
Source: Author's calculations.

The short-run measure for trade shows that trade liberalization in the previous two periods has no significant relationship with welfare. However, it does have a significant relationship with welfare after a three period lag. This indicates that trade liberalization policies do not have an immediate impact, but that their effect emerges over time. Thus, welfare or consumption does not respond to changes in trade in the short run. In the long run, there is a positive and significant relationship between trade and welfare. The coefficient estimate indicates that an increase in trade is associated with higher levels of welfare. This is as expected: trade liberalization enhances welfare in the long run once the positive benefits of opening up the economy to international markets emerge. The results suggest that, in the short run, countries may experience a decrease in consumption, perhaps due to increasing vulnerability as the economy opens up. In the long run, however, the benefits of openness – such as access to cheaper imports or greater availability of goods and services – become apparent.

The results for income indicate that it plays an important role in determining welfare. The positive relationship between income and welfare also holds in the long run, which indicates that an increase in GDP or income leads to an increase in household welfare or consumption. The third determinant of welfare or consumption is government expenditure. The results show that there is no relationship between the two variables either in the short run or long run. This implies that government policies of higher expenditure or providing direct assistance have an insignificant impact on welfare, which may point to the nature of government expenditures in Pakistan rather than their efficacy in general.

The results of this estimation reveal that both trade liberalization and GDP enhance welfare in Pakistan and that policy choices play an important role in determining welfare. However, this welfare-enhancing impact is not necessarily immediate, but emerges in the long term. The cointegrating vector captures the long-run relationship between the variables and (in matrix form) is written as

$$\hat{\prod} = \begin{pmatrix} 1, -0.773, 0.074, 1.73\mathrm{e}-18 \\ -5.33\mathrm{e}-15, 24.639, 21.011, 1 \end{pmatrix}$$

We test for autocorrelation among the residuals. The results given in Table 6 indicate that we cannot reject the null hypothesis of no autocorrelation for the two lags. Next, we test for the normality of the error terms using the Jarque–Bera test. The results indicate that we cannot reject the null hypothesis of normally distributed errors. Thus, the errors are not skewed and there is no kurtosis.

Table 6: Results of VECM stability tests for welfare model

Tests for stability check	Chi-sq. value	P-value of chi-sq.
Lagrange multiplier test* (lag 1)	8.954	0.91500
Lagrange multiplier test* (lag 2)	9.170	0.90600
Jarque–Bera test**	4.464	0.81302
Skewness	2.387	0.66494
Kurtosis	2.077	0.72162

Note: * = H_o (no autocorrelation at lag order). ** = H_o (error terms are normally distributed).
Source: Author's calculations.

4.2. Relationship Between Social Indicators and Trade Liberalization

In addition to analyzing welfare, we examine whether there is any correlation between trade liberalization and social indicators capturing poverty, education, health and inequality. Trade liberalization is expected to increase welfare and similarly to improve individuals' standard of living. The study's rationale is that, since trade liberalization is expected to improve exports and imports, this should be accompanied by increased employment opportunities, reduced poverty, increased school enrollment and better health outcomes. We do not focus on import and export performance since the literature already indicates their importance. To examine the relationship between trade liberalization and social indicators, we use data from the World Development Indicators. The welfare variables in equation (1) are replaced with social indicators, while the independent variables remain the same. The study aims to establish correlation rather than causation.

We use life expectancy to gauge health outcomes, measured by the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to remain constant throughout its life. Inequality is measured using World Bank estimates of the GINI index, defined as the extent to which the distribution of income among individuals or households within an economy deviates from a perfectly equal distribution. Education outcomes are measured by the total number of children enrolled at primary level in public and private schools. Finally, the depth and incidence of poverty is measured by the poverty gap at US$1.90 a day, defined as the mean shortfall in income or consumption relative to the poverty line and expressed as a percentage of the poverty line (where the nonpoor have a zero shortfall). All the variables are used in log form.

To estimate the model, we use the ADF test to check for stationarity. The results in Table 7 show that life expectancy is integrated of order 0, while primary enrolment, the poverty gap and the GINI index are integrated of order 1. We choose the appropriate model based on the ADF test and cointegration results.

Table 7: ADF test statistics

Variable	Level t-statistic	First-difference test statistic	Order of integration
Ln life expectancy (L)	-14.970***	–	I(0)
Ln primary enrolment (E)	-0.254	-6.697***	I(1)
Ln poverty gap (P)	-0.925	-4.905***	I(1)
Ln GINI index (GINI)	-2.591	-4.323***	I(1)

Note: If test statistic > critical value, we reject Ho of nonstationarity.
Source: Author's calculations.

Since life expectancy is integrated of order 0, while the independent variables are integrated of order 1 (as shown in Table 2), we select the autoregressive distributed lag model (ARDL) and select a lag length of 3.[5] Given that primary enrolment, the poverty gap and the GINI index are integrated of order 1, we also test for cointegration, the results of which are presented in Table 8. The primary enrolment and poverty gap models are cointegrated of rank 1 and, therefore, we estimate a VECM in both cases. Since the GINI index is not cointegrated, we estimate a vector autoregressive model (VAR) in this case.

Table 8: Cointegration test results (Johansen–Juselius maximum likelihood method)

			Cointegration test statistic for		
Null hypothesis	Alternative hypothesis	5% critical value	Primary enrolment	Poverty gap	GINI index
$r = 0$	$r > 0$	29.68	40.55	44.31	22.27*
$r \leq 1$	$r > 1$	15.41	14.83*	15.07*	7.36

Source: Author's calculations.

[5] Selected based on visual inspection.

Table 9 gives the lag order selection criteria used, according to which we select 4 as the lag length for primary enrolment, the poverty gap and the GINI index.

Table 9: Lag order selection criteria

	Primary enrolment			Poverty gap			GINI index		
Lags	**AIC**	**HQC**	**SBC**	**AIC**	**HQC**	**SBC**	**AIC**	**HQC**	**SBC**
0	-3.76	-3.70	-3.59	-2.58	-2.53	-2.38	-7.08	-7.04	-6.88
1	-11.84	-11.53	-10.99*	-8.20	-7.96	-7.21	-12.13	-11.93	-11.13
2	-11.76	-11.21	-10.24	-8.40	-7.98	-6.61	-12.67	-12.32	-10.88
3	-11.57	-10.78	-9.38	-8.62	-8.01	-6.04	-14.45	-13.94	-11.86
4	-12.30*	-11.2*	-9.43	-12.94*	-12.14*	-9.56*	-51.64*	-50.98*	-48.25*

Source: Author's calculations.

Table 10 gives the estimation results for the four social indicators, with life expectancy, primary enrolment, the poverty gap and the GINI index as the dependent variables. The lagged values of the dependent variables (represented by Z), income, government spending and trade liberalization and their lags are the independent variables.[6]

[6] All the independent variables are the same as used in Table 5.

Table 10: Short-run and long-run estimates of social indicators

	ARDL	VECM				VAR
	Life expectancy	Primary enrolment		Poverty gap		GINI index
Variable		Short run	Long run	Short run	Long run	
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{t-1}	2.240***	-0.234		0.527		0.364*
	(0.144)	(0.213)		(0.435)		(0.216)
Z_{t-2}	-1.646***	-0.190		0.504		-0.141
	(0.253)	(0.208)		(0.538)		(0.215)
Z_{t-3}	0.394***	-0.359*		0.343		-0.344**
	(0.118)	(0.209)		(0.507)		(0.162)
Z_{t-4}						-0.433***
						(0.167)
Y_{t-1}	-0.001	0.974	-4.828***	-2.646	4.971***	-1.540***
	(0.0009)	(0.834)	(0.399)	(8.847)	(0.221)	(0.375)
Y_{t-2}	0.003**	-0.930		4.498		2.040***
	(0.001)	(0.942)		(10.03)		(0.419)
Y_{t-3}	-0.002	-1.621*		10.51		0.0635
	(0.001)	(0.906)		(9.746)		(0.482)
Y_{t-4}						-0.401
						(0.366)
G_{t-1}	0.0001	0.577**	-0.848***	-2.613	2.187***	-0.284***
	(0.0003)	(0.250)	(0.272)	(1.878)	(0.159)	(0.077)
G_{t-2}	-0.00004	0.103		-0.862		0.101
	(0.0003)	(0.220)		(2.145)		(0.099)
G_{t-3}	-0.0003	0.298*		-1.098		0.117
	(0.0002)	(0.176)		(1.250)		(0.091)
G_{t-4}						0.129**
						(0.051)
T_{t-1}	0.0004	-0.359	4.547***	-1.493	-5.833***	0.108
	(0.0002)	(0.279)	(0.477)	(2.015)	(0.3265)	(0.103)
T_{t-2}	-0.0003	-0.339		2.236		0.213**
	(0.0002	(0.234)		(3.107)		(0.096)
T_{t-3}	0.0001	0.135		-0.776		-0.151
	(0.0002)	(0.195)		(3.282)		(0.128)
T_{t-4}						-0.483***
						(0.171)
Constant	0.0238	0.0141		-0.0223		8.885***
	(0.0155)	(0.0517)		(0.621)		(2.110)
ECT		0.155*		-0.677		
		(0.0884)		(0.424)		
R-squared	0.968	0.4116	–	0.5834	–	0.9167
Sample	1967–2015	1971–2014	1971–2014	1987–2012	1987–2012	1987–2010

Note: Dependent variables = life expectancy, primary enrolment, poverty gap and GINI index. Independent variables = lagged dependent variables, income, trade, government expenditure and lagged independent variables. All variables are used in log form. The ARDL model is estimated with three lags, the VECM in differenced form with rank 1 and four lags, and the VAR model with 4 lags. Sample size varies across estimations due to data availability. Standard errors given in parentheses. *** = 1 percent significance level, ** = 5 percent significance level and * = 10 percent significance level.
Source: Author's calculations.

Column (1) gives the results for the life expectancy variable, estimated using an ARDL model with three lags of each variable. The results show that trade liberalization has no significant correlation with life expectancy. Columns (2) and (3) give the short-run and long-run estimates of the VECM using primary enrollment as a dependent variable. The results show that trade liberalization does not have a significant correlation with primary enrollment in the short run, but has a positive and significant correlation in the long run. This is consistent with our earlier finding that it takes time for trade liberalization policy to affect welfare. We can also see that government spending has a positive and significant correlation with enrollment in the short run, but this correlation becomes negative in the long run. This has implications for policymaking with respect to education spending.

Columns 4 and 5 give the short-run and long-run results of the VECM using the poverty gap as the dependent variable. The results are similar to those for primary enrollment: trade liberalization is associated with a decline in poverty in the long run, but there is no significant correlation in the short run. Column 6 gives the results for the GINI index, estimated using a VAR model with a lag length of 4. The two year lagged trade variable has a positive correlation with inequality, but after four years, trade has a negative correlation with inequality. What we conclude from this is that, post-trade liberalization, inequality initially rises but after few years will fall. An interesting finding is that government spending may decrease inequality in the short run, but tends to increase inequality over time.

4.3. Discussion

The study's results show that trade liberalization policies do not have an immediate impact on welfare, education, poverty and inequality. Instead, their effects on welfare and other social indicators tend to emerge over time. The empirical literature supports the argument that liberalization does not have an adverse impact on welfare, although it is not the only channel through which poverty can be reduced. While trade liberalization implies significant distributional changes and may reduce welfare in the short run, it is likely to enhance welfare in the long run (Winters, McCulloch & McKay, 2004). The consensus is that liberalization boosts incomes and reduces poverty (Winters & Martuscelli, 2014).

Our empirical results differ somewhat with the literature for developed and developing countries. Ingco (1997), for instance, finds that liberalization leads to an increase in welfare; these welfare gains are higher for poorer households than for richer households in developed countries.

Federici and Montalbano (2010) find consistent evidence for the same argument in the case of developing countries. Looking at Bangladesh, Raihan (2010) shows that trade liberalization has a negative impact on welfare and GDP in the short run, while consumption tends to grow for all income groups. The benefits of trade liberalization are most pronounced for the poorest households. Our results, on the other hand, point to an increase in inequality in the short run, meaning the richer households benefit more from trade liberalization than poorer households.

Liberalization has also helped reduce wage inequality in India, for example (Kumar & Mishra, 2008). While there is consensus on the short-run loss that follows trade liberalization, this loss is smaller than the long-run gains that can be expected (Mishra & Topalova, 2007). Some studies, however, disagree. In Indian districts with a concentration of industries more exposed to liberalization, the incidence and depth of poverty fell by less than expected as a result of trade liberalization – a setback of about 15 percent of India's progress toward poverty reduction during the 1990s. Moreover, inequality remained unaffected for the sample of Indian states in both urban and rural areas (Topalova, 2007).

5. Conclusion

Policy choices play an important role in determining growth. To this end, most developing countries have initiated liberalization policies to reap the benefits of globalization. Indeed, a country's trade policy often reflects its overall policy choices with respect to growth and welfare.

This study examines the relationship between trade liberalization and welfare and other social indicators for Pakistan over the period 1986–2015. Despite the substantial literature examining the impact of economic growth and trade liberalization, few studies have looked at the relationship between welfare and trade liberalization. This study contributes to the literature by examining this relationship, using consumption to gauge welfare. It also measures the correlation between social indicators and trade liberalization to determine if the latter's benefits translate into consumption gains alone or if they are associated with improvements in education and health, and declining poverty and inequality.

The empirical results reveal that trade liberalization policy may have no effect (or in the case of income inequality, a negative effect) on welfare in the short run. Instead, its benefits emerge over time in terms of poverty reduction, declining inequality and an increase in enrollment. The benefits of trade liberalization may only be experienced after a number of years.

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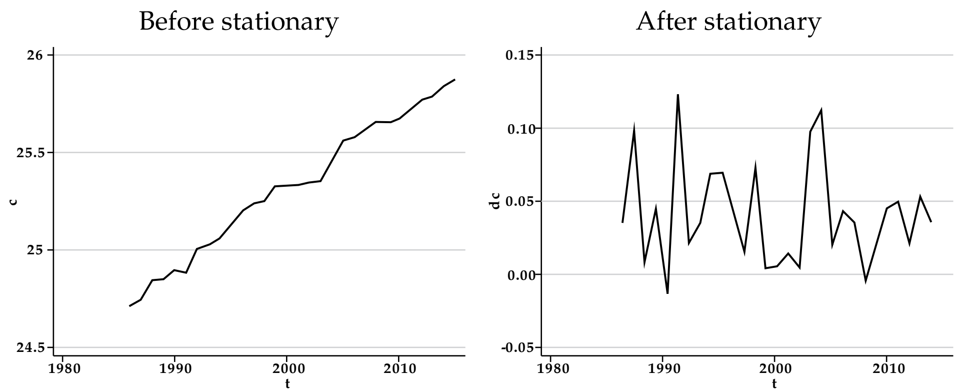
Appendix

Table A1: Phillips–Perron test statistics for welfare model

Variable	Level t-statistic	First-difference test statistic	Order of integration
Consumption (C)	3.137	-4.089***	I(1)
GDP (Y)	3.716	-2.641*	I(1)
Trade (T)	-0.658	-6.798***	I(1)
Government/GDP (G)	-1.785	-5.635***	I(1)

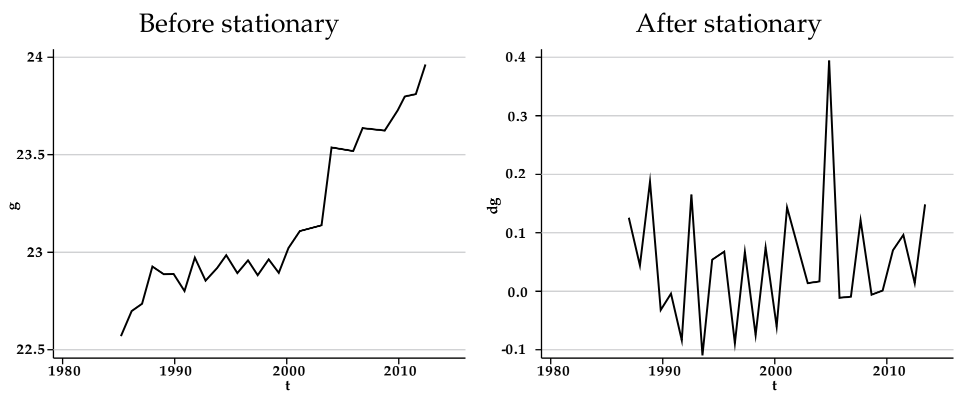
Note: Ho = nonstationarity. If test statistic > critical value, we reject Ho.

Figure A1: Ln of final consumption expenditure, 1968 to 2012



Source: Author's illustration.

Figure A2: Ln of government expenditure, 1968 to 2012

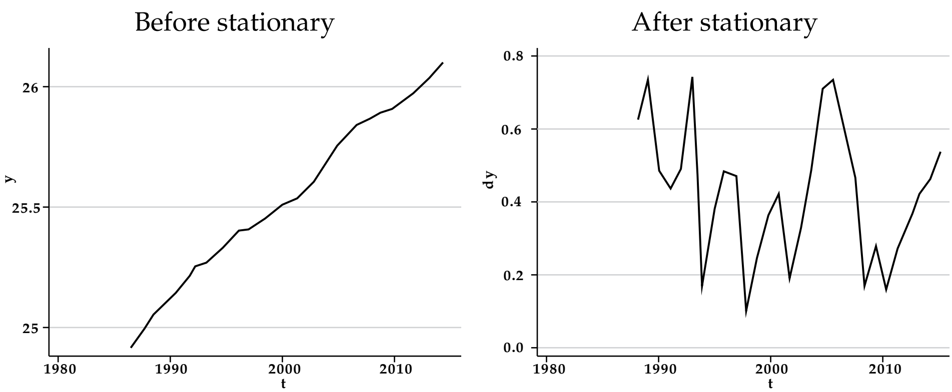


Source: Author's illustration.

Figure A3: Ln of trade, 1968 to 2012

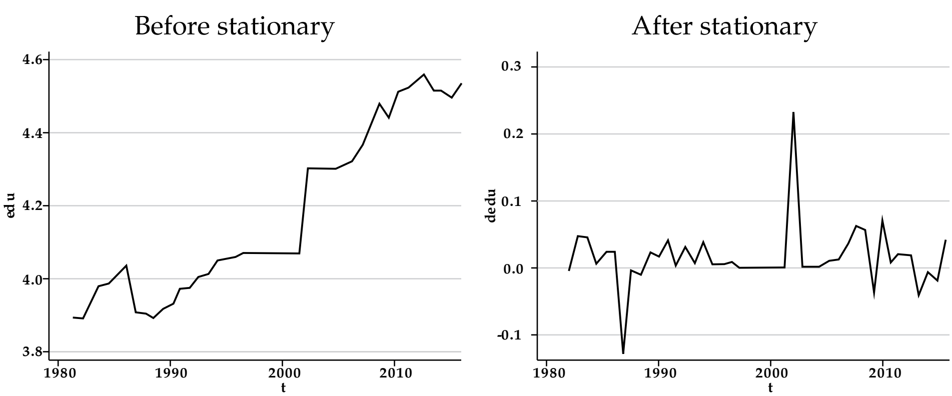
Source: Author's illustration.

Figure A4: Ln of income, 1968 to 2012



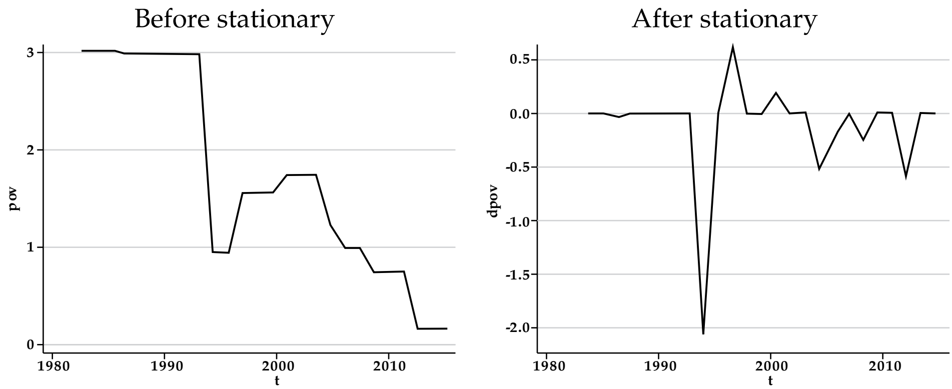
Source: Author's illustration.

Figure A5: Ln of primary enrolment, 1971 to 2014



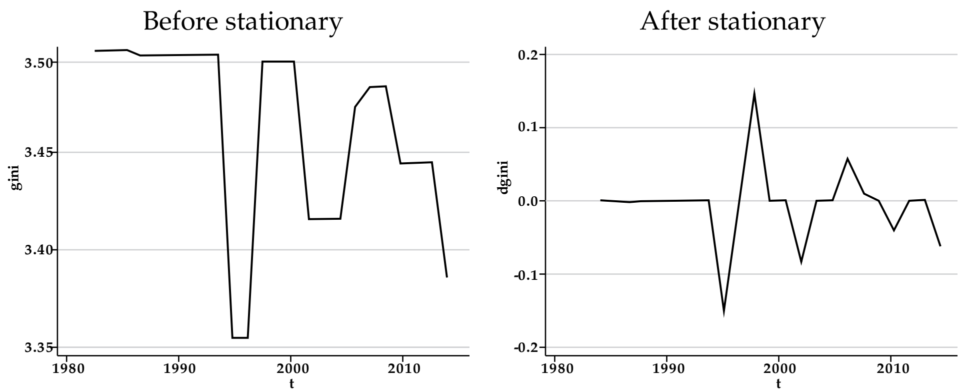
Source: Author's illustration.

Figure A6: Ln of poverty gap, 1987 to 2012



Source: Author's illustration.

Figure A7: Ln of GINI index, 1987 to 2010



Source: Author's illustration.

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Testing the Dynamic Linkages of the Pakistani Stock Market with Regional and Global Markets

Zohaib Aziz* **and Javed Iqbal****

Abstract

This article examines the dynamic linkages between Pakistan's emerging stock market and (i) the US market and (ii) the regional markets of India and Japan. Using data for the daily returns and volatility spillovers of three market pairs (Pakistan-US, Pakistan-Japan and Pakistan-India), the study estimates a series of bivariate asymmetric VARMA(1,1)-GARCH(1,1) models. It also fits multivariate asymmetric VARMA(1,1)-GARCH(1,1) models for two groups of markets: Pakistan-India-US and Pakistan-India-Japan. Based on the mean spillovers, the results suggest that the global and regional equity markets (Granger) cause the Pakistani market. There are unidirectional volatility spillovers to Pakistan from the US and Japan, while India is the only regional market with a significant cross-asymmetric effect on Pakistan. In the multivariate case, the regional and global markets have significant joint mean and variance spillovers and asymmetric effects on the Pakistani market. This indicates a weak degree of integration between the Pakistani market and the global and regional markets, implying that local risk factors – either firm-specific or country-specific – explain the expected returns on investment in the Pakistani stock market.

Keywords: Dynamic linkages, bivariate GARCH, financial market integration.

JEL classification: G15, F65.

1. Introduction

The increasing integration of international financial markets has attracted the attention of financial analysts, multinational and domestic firms, investors, traders, portfolio managers, researchers, governments,

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international economic and financial policymakers and market regulators. Stock market integration occurs when the stock markets of different countries move in tandem, i.e., their returns and volatility are driven by common shocks. These dynamic linkages may be weak or strong and the degree of interdependence explains whether investors can move easily between markets and whether there are arbitrage opportunities to be availed (Jawadi & Arouri, 2008).

Investigating the strength and direction of co-movements between international stock markets is an important area of research. Several factors drive the integration of international markets, including (i) an increase in international trade and finance between national economies; (ii) open-door policies of liberalization that allow international investors to participate in local markets; (iii) technological advancements in communication and the gradual elimination of limits in capital flows; and (iv) the contagion effects of international financial crises. Analyzing the integration of stock markets may be useful for asset pricing and allocation, risk diversification, trading and hedging strategies, and the regulation of capital markets.

Analyzing the extent of integration helps gauge risk reduction through portfolio diversification. When a national market is weakly integrated with global markets, the transmission of returns and volatility shocks is limited. Thus, the inclusion of such weakly integrated markets in an investment portfolio gives international investors the benefits of diversification. In contrast, when markets are fully integrated, international financial and economic conditions strongly influence domestic markets. This increases the risk exposure of portfolios and limits the diversification benefits to international investors. Thus, investors tend to seek portfolios including stock markets that are not integrated or are weakly integrated with global markets so that the portfolio risk is smaller.

Stock market integration also has important implications for market efficiency. If the past returns of a stock market can be used to predict changes in other stock markets, then we cannot consider a semi-strong form of market efficiency to hold, according to Fama's (1970) classifications. Emerging markets tend to have higher levels of volatility and associated returns than developed markets (Iqbal, 2012). The linkages between emerging markets and mature markets make the former more sensitive and volatile. These linkages and transmissions are analyzed using the mean returns and volatility spillovers.

It is also worth investigating which mature or developing markets are closely linked to local emerging markets. Accordingly, the interdependency of emerging markets with global and regional markets is an important area in the finance literature. More recently, technological developments have become an additional channel of financial market linkages, making the regulation of financial markets more challenging as regulators must keep an eye on external developments. Studying dynamic linkages becomes especially important in crisis periods (e.g., the recent global financial crisis of 2008) when the intensity of external linkages is increased.

Very few studies in this area are based on South Asia. Specifically, there is little literature analyzing the linkages between markets at global and local levels with Pakistan as a base market and using rigorous econometric modeling such as the multivariate GARCH (MGARCH) approach. Barring a few studies, the literature provides no detailed testing of own and cross-mean and volatility spillovers between markets. The extent and magnitude of spillovers and the direction of linkages has not been systematically investigated in this context, nor have models been compared in the analysis of integration effects.

Given this, our objective is to analyze the integration of emerging stock markets, specifically the linkages between Pakistan and other developed and developing stock markets (global and regional markets), including spillover magnitude and direction. This study gauges the extent to which the Pakistani stock market is influenced by global markets (the US), neighbor developing markets (India) and regional developed markets (Japan).

We include the US market, given its leading role in world financial markets and the 'global center hypothesis', which argues that global centers such as the US market play a major role in the transmission of shocks (Li, 2007). As a large regional market, India has attracted investors' attention in recent years. Iqbal (2012) reports that the correlation between the Pakistani and Indian markets is 0.26, which he deems nontrivial. It is also the second largest magnitude of correlation between Pakistan and the other countries in his sample. Given the size and importance of the Indian market, one would expect some shocks to the Pakistani market from global markets to be transmitted via the Indian market. Finally, Japan is a regional developed market and it is worth investigating whether volatility spillovers into Pakistan are more likely to be transmitted from a global center (the US) or a regional center (Japan).

To achieve this objective, we use market pairs with Pakistan in a bivariate GARCH model and groups of countries with Pakistan in a trivariate model. We focus on the largest Pakistani stock market, the Karachi Stock Exchange (KSE), in which the KSE 100 is the most important index tracking aggregate stock price movement in Pakistan.

Iqbal (2012) provides an overview of the Pakistani stock market, explaining how it is integrated with world markets. He also examines correlation, pricing errors, cointegration and vector autoregressive (VAR) techniques used by other studies to measure integration in different periods. Earlier market integration analyses have used different versions of asset pricing models, while more recent studies tend to rely on econometric techniques (Chancharat, 2009). The literature on stock market integration, therefore, draws frequently on asset pricing models, Granger causality and cointegration techniques, factor analysis and GARCH models.

Some studies assume a linear dependence between markets and employ tests based on the constant correlation of index returns. However, the idea of time variations in volatility has now become more common, implying that stock market integration involves both linear and nonlinear dependence. Increasing stock market volatility is manifested in large stock price changes with either sign (Schwert, 1990). Accordingly, we employ a bivariate GARCH model that estimates linear and nonlinear dependence simultaneously to model mean returns and volatility.

The remaining article is organized as follows. Section 3 describes the methodology used. The data and primary diagnostics are given in Sections 4 and 5. Section 6 presents the study’s results. Section 7 concludes.

2. Literature Review

Sharma and Seth (2012) provide a comprehensive literature review of stock market integration in which they characterize empirical studies by year, country, the number of countries comprising the study sample, the number of years considered in the sample dataset and the econometric and noneconometric methodologies adopted for the data analysis. They find that, although the literature has looked at stock market integration since the 1980s, the bulk of this work has been done in the last few years.

Despite the rising number of empirical studies on stock market integration, most studies have focused on developed – rather than emerging – markets. This can entail determining mean returns, volatility spillovers and the cross-market effect of the same country and different countries, using an MGARCH model.[1] Several studies, however, examine the transmission of returns and volatility shocks from developed markets to Asian markets. These are outlined below.

Li (2007) tests the transmission of returns and volatility between the emerging stock market of China, the regional developed market of Hong Kong and the US global market, using a BEKK-MGARCH model. He finds no direct linkage between the Chinese and US markets and a unidirectional weak relationship with the Hong Kong market. Worthington and Higgs (2004) find nonhomogenous mean spillovers from developed markets and higher own-volatility spillovers compared to cross-volatility spillovers for the East and Southeast Asian markets, using a VAR(1)-BEKK(1,1) model.

Using an MGARCH model, Chou, Lin and Wu (1999) find significant volatility spillovers from the US stock market to the Taiwan stock market, primarily in the close-to-open returns case. Miyakoshi's (2003) empirical results indicate that Asian markets are subject to a greater regional (Japan) influence than global (US) influence. In addition, the signals from a market that opens earlier provide useful information to Asian and international investors in terms of earning profits. In contrast to Miyakoshi, Li and Giles (2015) use an MGARCH model and find unidirectional shock and volatility spillovers from the US market to both the Japanese and Asian emerging markets.

Some studies focus on the dynamic linkages of European markets with major world markets. Li and Majerowska (2008) model and test the dynamic linkages between the emerging stock markets of Poland and Hungary and the developed markets of Germany and the US. They use a four-variable asymmetric GARCH-BEKK model and find evidence of weak integration among these markets. Saleem (2009) also uses a GARCH-BEKK model to investigate the relationship between the Russian equity market and world markets; he finds there is partial integration between the two.

Other studies use a geographically broader set of markets. Beirne et al. (2010) examine the mean and volatility spillovers of global and regional markets for a sample of 41 local emerging stock markets in Asia, Europe, Latin America and the Middle East. They analyze cross-market effects using tri-variate VAR-GARCH(1,1)-in-mean models and report significant spillovers from global and regional markets to local emerging markets.

[1] See Sharma and Seth (2012) and Chancharat (2009) for a detailed analysis of stock market integration.

Kumar (2013) applies a VAR and MGARCH model to investigate the relationship of mean and volatility spillovers between stock prices and exchange rates for India, Brazil and South Africa. Using daily data, he finds evidence of bidirectional volatility spillovers in the stock and foreign exchange markets and argues that stock markets play a relatively important role in these spillovers.

In contrast to the studies above, which focus on linkages in emerging markets in Asia, Europe and Latin America, Karolyi (1995) uses a bivariate GARCH model to test the transmission of stock returns and volatility between two neighboring developed markets – Canada and the US. He finds far weaker returns and volatility spillovers in later sub-periods, especially for those Canadian stocks that are listed dually on the New York Stock Exchange.

3. Methodology

We examine the bivariate and tri-variate linkages between Pakistan and three other stock markets – the US (a global developed market), Japan (a regional developed market) and India (a neighboring developing market) – to gauge the extent of regional and global integration effects on the former. This entails estimating and testing the mean returns and volatility spillovers between pairs of markets: Pakistan-US, Pakistan-Japan and Pakistan-India, using a bivariate GARCH model, and Pakistan-India-US and Pakistan-India-Japan, using an MGARCH model.

3.1. MGARCH Model

The MGARCH model is a useful tool to capture the transmission effects of mean and volatility spillovers between stock markets. It enables one to model and predict the time-varying volatility and volatility co-movements of multivariate time series (Zivot & Wang, 2005). Most MGARCH applications are related to asset returns and exchange rates.

Several specifications of the conditional variance-covariance matrix of the MGARCH model are used to capture integration effects.[2] The BEKK model proposed by Engle and Kroner (1995) is an important specification of the MGARCH conditional variance-covariance, a key feature being its positive definiteness. However, as Tse and Tsui (2002) point out, interpreting the BEKK model parameters is not as easy as for other

[2] See Bauwens, Laurent and Rombouts (2006) for a survey of different specifications of the MGARCH model.

MGARCH modifications. Moreover, its accumulated effects on future variances and covariances are difficult to determine. Nonetheless, it remains a popular model, which this study uses to examine volatility dynamics.

Black (1976) argues that, with the same absolute magnitude, negative shocks have a larger impact on volatility than positive shocks – this is termed the leverage effect. Similarly, in the multivariate case, the variances and covariances may respond differently to positive and negative shocks (see Bauwens et al., 2006). Accordingly, Kroner and Ng (1998) propose an extension of the BEKK model that allows for the leverage effect. A bivariate VARMA(1,1)-BEKK(1,1) model allowing asymmetric effects is given as follows:

$$R_t = \Lambda + \Psi R_{t-1} + \Omega u_{t-1} + u_t,\ u_t | I_{t-1} \sim (0, H_t) \quad (1)$$

$$H_t = \Gamma'\Gamma + \Theta' u_{t-1} u'_{t-1} \Theta + \Phi' H_{t-1} \Phi + D' \xi_{t-1} \xi'_{t-1} D \quad (2)$$

$R_t = [r_{1,t}\ r_{2,t}]'$ is the percentage log-returns vector. $u_t = [u_{1,t}\ u_{2,t}]'$ is the residual vector with a conditional variance-covariance matrix $H_t = [h_{ij,t}]_{i,j=1,2}$. ξ_t is equal to u_t if u_t is negative and 0 otherwise. The set of information available at time $t-1$ is expressed by I_{t-1}. $\Lambda = [\lambda_1\ \lambda_2]'$, $\Psi = [\psi_{ij}]_{i,j=1,2}$ and $\Omega = [\omega_{ij}]_{i,j=1,2}$ are the coefficient matrices of constant terms, first-lagged returns and first-lagged shocks for the mean returns, respectively. The parameter matrix of volatility equation (2) is denoted by $\Gamma = [\gamma_{ij}]_{i,j=1,2}$, which is an upper triangular matrix. $\Theta = [\theta_{ij}]_{i,j=1,2}$ and $\Phi = [\phi_{ij}]_{i,j=1,2}$ are unrestricted ARCH and GARCH coefficient matrices, respectively. $D = [d_{ij}]_{i,j=1,2}$ is the unrestricted coefficient matrix of the asymmetric response of volatility (see the Appendix for the model in expanded notation).

Equation (1) is used to assess the own and cross-mean returns spillover; equation (2) captures the own and cross-volatility spillover of the stock market. We use a multivariate student t-distribution for the residuals of the model.

3.2. Estimation

The parameters of the BEKK-MGARCH model are estimated by computing the multivariate conditional log-likelihood function $L(\Omega)$ given by:

$$L_t(\Omega) = -log 2\pi - \frac{1}{2} log|H_t| - \frac{1}{2} u'_t(\Omega) H_t^{-1}(\Omega) u_t(\Omega) \quad (3)$$

$$L(\Omega) = \sum_{t=1}^{T} L_t(\Omega) \tag{4}$$

where Ω represents the vector of all unknown parameters and T is the total number of observations of each series of returns vector R_t. The Berndt–Hall–Hall–Hausman numerical maximization algorithm is used to produce the maximum likelihood estimates of the parameters and associated standard errors.

3.3. Model Diagnostics: Multivariate Portmanteau Test

Hosking (1980) generalizes the univariate Ljung–Box test into a multivariate version – the multivariate portmanteau test, which considers all series simultaneously rather than separately as well as cross-moment serial correlations. The Hosking test statistic testing for no correlation, autocorrelation and cross-correlation in the residual vector series u_t is given by:

$$Q_{k(m)} = T^2 \sum_{l=1}^{m} \frac{1}{T-l}\, tr\left(\hat{\Xi}_l' \hat{\Xi}_0^{-1} \hat{\Xi}_l \hat{\Xi}_0^{-1}\right) \tag{5}$$

where k is the dimension of returns vector R_t, T is the total number of observations, m is the maximum lag length and $tr(.)$ is the trace function of the matrix, which is the sum of the diagonal elements of a square matrix. The estimated correlation matrix at lag $-l$ is denoted by $\hat{\Xi}_l = \left[\hat{\xi}_{ij}\right]_{i,j=1,2}$. Assuming the null hypothesis holds, $Q_{k(m)}$ follows asymptotically a chi-squared distribution with (k^2m) degrees of freedom. We use the multivariate Ljung-Box test to gauge the model's adequacy.

3.4. Hypothesis Test (Wald Test)

The following Wald test is used to test the mean and volatility spillover and cross-market asymmetric response of volatility:

$$W = [S\hat{\beta}]'\left[S\, var(\hat{\beta})S'\right]'\left[S\hat{\beta}\right] \sim \chi^2(q) \tag{6}$$

where S is the parameter restriction matrix of order (dimension) q x k, q is the number of restrictions and k is the number of regressors. β is a vector of estimated parameters of order (k x 1) and var (β) is the heteroskedasticity-robust consistent estimator for the covariance matrix of the parameter estimates.

3.5. Mean and Volatility Spillover Tests

We present 20 hypotheses, 16 of which represent all the pairs of countries – including a benchmark case and three mean and volatility spillover and cross-market asymmetric response cases – and four multivariate cases. The first parameter subscript denotes the Pakistani market. The second subscript denotes the country included in that pair. In the multivariate case, subscripts 1, 2 and 3 represent Pakistan, India and the US/Japan, respectively. Using the parameter notations given in the Appendix, we test the following hypotheses:

Joint tests of spillover in mean and variance and cross-market asymmetric effect

H01: No spillover in mean, no spillover in variance and no cross-market asymmetric effect: $\psi_{12} = \psi_{21} = \omega_{12} = \omega_{21} = \theta_{12} = \phi_{12} = \theta_{21} = \phi_{21} = d_{12} = d_{21} = 0$

Tests of spillover in mean

- H02: No mean spillover: $\psi_{12} = \psi_{21} = \omega_{12} = \omega_{21} = 0$
- H03: No mean spillover from the second market to the first: $\psi_{12} = \omega_{12} = 0$
- H04: No mean spillover from the first market to the second: $\psi_{21} = \omega_{21} = 0$

Tests of spillover in variance

- H05: No volatility spillover: $\theta_{12} = \phi_{12} = \theta_{21} = \phi_{21} = 0$
- H06: No volatility spillover from the second market to the first: $\theta_{12} = \phi_{12} = 0$
- H07: No volatility spillover from the first market to the second: $\theta_{21} = \phi_{21} = 0$
- H08: No ARCH effect spillover: $\theta_{12} = \theta_{21} = 0$
- H09: No ARCH volatility spillover from the second market to the first: $\theta_{12} = 0$
- H10: No ARCH volatility spillover from the first market to the second: $\theta_{21} = 0$
- H11: No GARCH volatility spillover: $\phi_{12} = \phi_{21} = 0$

- H12: No GARCH volatility spillover from the second market to the first: $\phi_{12} = 0$
- H13: No GARCH volatility spillover from the first market to the second: $\phi_{21} = 0$

Tests of cross-market asymmetric effect in variance

- H14: No cross-market asymmetric response: $d_{12} = d_{21} = 0$
- H15: No cross-market asymmetric response from the second market to the first: $d_{12} = 0$
- H16: No cross-market asymmetric response from the first market to the second: $d_{21} = 0$

Tests for multivariate case

- H17: No spillover in mean, variance and cross-market asymmetric effect on the Pakistani market: $\psi_{12} = \psi_{13} = \omega_{12} = \omega_{13} = \theta_{12} = \phi_{12} = \theta_{13} = \phi_{13} = d_{12} = d_{13} = 0$
- H18: No joint mean spillover from the regional and global markets to the Pakistani market: $\psi_{12} = \psi_{13} = \omega_{12} = \omega_{13} = 0$
- H19: No joint volatility spillover from the regional and global markets to the Pakistani market: $\theta_{12} = \phi_{12} = \theta_{13} = \phi_{13} = 0$
- H20: No joint cross-market asymmetric response from the regional and global markets to the Pakistani market: $d_{12} = d_{13} = 0$

These 20 hypotheses are performed to test the own and cross-mean and volatility spillovers and determine any linear and nonlinear dynamic linkages between the Pakistani market and the other markets. Since dynamic linkages can stem from different sources, it is important to test this aspect. In this respect, the study provides a much broader coverage of tests than earlier studies.

4. Data

The sample of countries being tested for their relationship with Pakistan are India, the US and Japan. We use the daily closing index prices on the KSE 100 (Karachi Stock Exchange), the BSE Sensex 30 (Bombay Stock Exchange), the Nikkei 225 (Tokyo Stock Exchange) and the S&P 500 (New York Stock Exchange) to represent the stock markets of Pakistan, India, Japan and the US, respectively. The data for each country consists of 3,115 value-weighted index observations – the closing prices adjusted for dividends and splits – for the period 3 July 1997 to 13 November 2012. We delete all same-date observations for these markets if any observation is missing on account of no trading. Thus, we consider the observations for those dates on which all the markets were open. The percentage daily log returns for the given indices are employed by taking the first difference of the log indices and multiplying them by 100, i.e., $r_t = (lnP_t - lnP_{t-1}) \times 100$.

All the data has been obtained from Datastream. Given that Japan is part of this study, it is worth noting that the Asian financial crisis of 1997 may render the estimation less useful. However, on rechecking the results after excluding the crisis period by starting the sample from January 1998, we find there is no significant change.

5. Descriptive Statistics and Primary Diagnostics

Table 1 reports the percentage daily log returns for the four stock markets. We can see that the average returns for the emerging markets in the sample are greater than those for the developed markets. Pakistan has the highest average return (0.025 percent) and Japan the lowest (–0.020 percent). As evident from the standard deviations, India is found to be the most volatile market with a standard deviation of 1.63 percent, while the US market is the least volatile, with a standard deviation of 0.58 percent. Barring India, the market returns exhibit negative skewness, indicating that large negative stock returns are more common than large positive returns.

The kurtosis results in Table 1 show that the distributions of the emerging markets, Pakistan and India, are more leptokurtic than those of the developed markets, the US and Japan. This excess kurtosis indicates that extreme returns or outliers appear more frequently in emerging markets than in developed ones. The Jarque–Bera statistics reflect the nonnormality of all four distributions. The descriptive statistics reported here endorse the stylized facts of financial returns. The GARCH model is equipped to deal with data that exhibits this feature. Moreover, the nonzero skewness suggests an ARCH order greater than 1 (see Li, 2007). The GARCH(1,1), which is equivalent to an ARCH(∞) model, is a parsimonious statistical model.

Table 1: Percentage daily log returns, 3 July 1997 to 13 November 2012

	Pakistan	India	Japan	US
Mean	0.025	0.045	-0.020	0.001
Median	0.057	0.098	-0.005	0.026
Maximum	5.542	15.989	7.655	2.663
Minimum	-5.738	-11.809	-11.153	-4.003
Standard deviation	0.723	1.632	1.487	0.538
Skewness	-0.347	0.119	-0.308	-0.377
Kurtosis	8.920	8.616	6.111	6.941
Jarque-Bera statistic	4,612.299	4,101.286	1,305.638	2,090.471
P-value	0.000	0.000	0.000	0.000

Source: Authors' estimates.

6. Results and Discussion

Our analysis is based on the results presented in Tables 2 and 3. Table 2 reports the estimated results for the bivariate asymmetric VARMA(1,1)-GARCH(1,1) models with BEKK specifications for three pairs of markets – Pakistan-US, Pakistan-India and Pakistan-Japan – using a multivariate student t-distribution of errors. The results are divided into three panels: panels A and B give the estimates and standard errors of AR, MA, ARCH, GARCH and the asymmetric coefficient matrices, while panel C reports the diagnostics of the estimated models. The multivariate Ljung–Box Q statistics for the third and sixth orders in squared standardized residuals show that there is no serial dependence in the latter. This indicates that the fitted variance-covariance equations are appropriate for all the pairs.

6.1. Mean Equation Analysis

Panel A of Table 2 shows that current returns are significantly predicted by past-day returns in the Pakistani market. The returns have positive first-order autocorrelation, which is evident from all the pairs of countries. The magnitude of past lags ranges from 0.9 to 0.977. The Pakistani market has significant mean reversion as yesterday's unexpected positive shock decreases today's return significantly. The effect (response) of the previous day's shock on current returns ranges from 0.86 to 0.94.

Table 2: Estimated coefficients for bivariate asymmetric GARCH model and its diagnostics

Parameter	VARMA(1,1)-BEKK(1,1)		
	Pakistan-US	**Pakistan-India**	**Pakistan-Japan**
Panel A: Estimated coefficients of mean equations			
λ_1	0.002	0.008***	0.011**
	(0.002)	(0.004)	(0.005)
λ_2	0.005	0.0454	0.061***
	(0.004)	(0.036)	(0.034)
ψ_{11}	0.901*	0.975*	0.977*
	(0.029)	(0.066)	(0.066)
ψ_{12}	0.214	-0.101	-0.112
	(0.139)	(0.091)	(0.078)
ψ_{21}	0.052	0.610	0.481
	(0.040)	(0.390)	(0.397)
ψ_{22}	0.514*	-0.186	-0.073
	(0.182)	(0.246)	(0.216)
ω_{11}	-0.863*	-0.940*	-0.933*
	(0.033)	(0.070)	(0.069)
ω_{12}	-0.155	0.121	0.127
	(0.130)	(0.095)	(0.082)
ω_{21}	-0.055	-0.612	-0.444
	(0.042)	(0.388)	(0.396)
ω_{22}	-0.563*	0.268*	0.162
	(0.175)	(0.242)	(0.215)
Panel B: Estimated coefficients of variance and covariance equations			
γ_{11}	0.118*	0.129*	0.126*
	(0.010)	(0.009)	(0.010)
γ_{21}	-0.009	-0.030	0.091***
	(0.010)	(0.043)	(0.053)
γ_{22}	0.052*	0.310*	0.435*
	(0.006)	(0.028)	(0.035)
θ_{11}l	0.370*	0.326*	0.355*
	(0.025)	(0.025)	(0.025)
θ_{21}	0.078*	0.001	0.021*
	(0.017)	(0.008)	(0.007)
θ_{12}	0.023***	-0.118**	-0.195*
	(0.012)	(0.047)	(0.055)
θ_{22}	0.055***	-0.140*	0.192*
	(0.033)	(0.029)	(0.024)
ϕ_{11}	0.882*	0.883*	0.892*
	(0.008)	(0.009)	(0.009)

Parameter	VARMA(1,1)-BEKK(1,1)		
	Pakistan-US	Pakistan-India	Pakistan-Japan
ϕ_{21}	0.015**	0.007***	-0.010**
	(0.007)	(0.003)	(0.004)
ϕ_{12}	-0.001	-0.006	0.012
	(0.006)	(0.024)	(0.026)
ϕ_{22}	0.958*	0.916*	0.877*
	(0.003)	(0.008)	(0.012)
d_{11}	0.337*	0.407*	0.340*
	(0.039)	(0.035)	(0.036)
d_{21}	0.009	-0.018***	-0.009
	(0.030)	(0.010)	(0.011)
d_{12}	-0.006	0.084	0.262*
	(0.014)	(0.058)	(0.061)
d_{22}	-0.362*	0.450*	0.427*
	(0.019)	(0.029)	(0.032)
Panel C: Diagnostics			
LB(3)	12.401	7.252	15.741
	(0.414)	(0.840)	(0.203)
LB(6)	21.892	19.072	24.211
	(0.585)	(0.748)	(0.449)
LB2(3)	16.466	6.496	28.416
	(0.170)	(0.889)	(0.004)
LB2(6)	24.150	13.448	40.024
	(0.453)	(0.958)	(0.021)
Log likelihood	-4,685.834	-8,184.977	-8,207.943
AIC	9,423.668	16,421.955	16,467.887
BIC	9,580.803	16,579.090	16,625.022

Note: *, **, *** = significant at 1, 5 and 10 percent, respectively. P-values given in parentheses.
LB and LB2 = multivariate Ljung-Box (portmanteau test) statistics for standardized and squared standardized residuals, respectively.
Source: Authors' estimates.

The cross-market return spillovers are captured by the off-diagonal parameters ψ_{12} and ψ_{21} of matrix Ψ and ω_{12} and ω_{21} of matrix Ω. The coefficients indicate that the regional and global markets have no significant impact on Pakistani returns. Similarly, no regional or global market return is influenced by the Pakistani market. The magnitude of the sum $(\psi_{12} + \omega_{12})$ indicates the extent of anticipated and unanticipated shocks from the regional and global markets to the Pakistani market. These magnitudes show that a 1 percent increase in the past day's returns and shocks from the

US, India and Japan increase current Pakistani returns by 0.0588 percent, 0.02 percent and 0.015 percent, respectively. The multivariate Ljung–Box Q statistics for standardized residuals of the third and sixth orders (panel C, Table 2) indicate the appropriate specification of the mean equation for all considered cases. We also test the VAR models for mean equations of different orders, but their diagnostics are not satisfactory. The VARMA(1,1) model is found to be properly specified.

To ascertain the effect of the past day's own and cross-market anticipated and unanticipated shocks on current returns, we test several hypotheses. The results are reported in panels A and B of Table 3. The first question is whether any sort of local or foreign anticipated or unanticipated shocks affect current Pakistani returns. This hypothesis (H01) is easily rejected for all cases, which implies that the bivariate GARCH model is more suitable than the univariate GARCH model. The latter will be misspecified in the presence of significant cross-market effects.

Table 3: Wald test for restrictions on bivariate asymmetric GARCH model

Hypothesis	Testing for restrictions		
	Pakistan-US	**Pakistan-India**	**Pakistan-Japan**
Panel A: Testing the combined restriction for mean and variance spillover and no cross-market asymmetric effect (benchmark testing)			
H01: No spillover in mean and variance and no cross-market asymmetric effect			
$\psi_{12} = \psi_{21} = \omega_{12} = \omega_{21} = \theta_{12} = \phi_{12} = \theta_{21} = \phi_{21} = d_{12} = d_{21} = 0$	62.924* (0.000)	43.427* (0.000)	38.572* (0.000)
Panel B: Wald test for testing the restrictions in mean equations of VARMA(1,1)			
H02: No overall mean spillover			
$\psi_{12} = \psi_{21} = \omega_{12} = \omega_{21} = 0$	21.260*	27.234*	17.441*
	(0.000)	(0.000)	(0.001)
H03: No mean spillover from the second market to the first			
$\psi_{12} = \omega_{12} = 0$	20.238*	20.849*	13.074*
	(0.000)	(0.000)	(0.001)
H04: No mean spillover from the first market to the second			
$\psi_{21} = \omega_{21} = 0$	1.672	2.478	4.122
	(0.433)	(0.289)	(0.127)

Hypothesis	**Testing for restrictions**		
	Pakistan-US	**Pakistan-India**	**Pakistan-Japan**
Panel C: Testing the restrictions in BEKK(1,1) variance and covariance equations			
H05: No volatility spillover			
$\theta_{12} = \phi_{12} = \theta_{21} = \phi_{21} = 0$	37.352*	14.720*	7.401
	(0.000)	(0.005)	(0.116)
H06: No volatility spillover from the second market to the first			
$\theta_{12} = \phi_{12} = 0$	29.826*	3.884	5.501***
	(0.000)	(0.143)	(0.063)
H07: No volatility spillover from the first market to the second			
$\theta_{21} = \phi_{21} = 0$	7.197**	11.686*	1.699
	(0.027)	(0.002)	(0.427)
H08: No ARCH effect/spillover			
$\theta_{12} = \theta_{21} = 0$	23.653*	6.118**	6.621**
	(0.000)	(0.046)	(0.036)
H09: No ARCH effect spillover from the second market to the first			
$\theta_{12} = 0$l	20.279*	0.021	5.264**
	(0.000)	(0.883)	(0.021)
H10: No ARCH effect spillover from the first market to the second			
$\theta_{21} = 0$	3.745**	6.106**	1.164
	(0.052)	(0.013)	(0.280)
H11: No GARCH effect/volatility spillover			
$\phi_{12} = \phi_{21} = 0$	3.970	3.738	1.743
	(0.137)	(0.154)	(0.418)
H12: No GARCH effect/volatility spillover from the second market to the first			
$\phi_{12} = 0$	3.949**	3.738***	1.710
	(0.046)	(0.053)	(0.190)
H13: No GARCH effect/volatility spillover from the first market to the second			
$\phi_{21} = 0$l	0.088	0.061	0.062
	(0.765)	(0.804)	(0.802)
H14: No cross-market asymmetric response			
$d_{12} = d_{21} = 0$	0.317	5.415***	1.267
	(0.853)	(0.066)	(0.530)
H15: No cross-market asymmetric response from the second market to the first			
$d_{12} = 0$	0.093	3.207***	0.696
	(0.759)	(0.073)	(0.403)
H16: No cross-market asymmetric response from the first market to the second			
$d_{21} = 0$	0.225	2.056	0.583
	(0.635)	(0.151)	(0.444)

Note: *, **, *** = significant at 1, 5 and 10 percent, respectively. P-values given in parentheses.
Source: Authors' estimates.

The hypothesis of no mean returns spillover to or from any of the local or foreign markets (H02) is rejected at 1 percent for all pairs of countries. The direction of this spillover effect is tested next. The hypothesis of a mean spillover (H03) from the second market to the Pakistani market is rejected, which implies that Pakistani market returns are significantly influenced by regional and global market shocks. As expected, the Pakistani market does not appear to have a significant influence on regional or global market returns (H04). This result makes sense, given that Pakistan is a far smaller market than the others.

As the World Bank data indicates, Pakistan's market capitalization-to-GDP ratio in 2012 was 19.5 percent, compared to 61.8 percent, 68 percent and 115.5 percent for Japan, India and the US, respectively.[3] Moreover, Pakistan's economy is smaller than these economies. Next, we look at the spillover direction, which indicates unidirectional Granger causality from the regional and foreign market returns to the Pakistani market returns. This implies that the Pakistani market is not a semi-strong efficient form because it is affected by regional and global financial conditions. Since the magnitude of the mean spillover from the US market to the Pakistani market is greater than that of the regional market, our results are consistent with the global center hypothesis, which implies that a global center such as the US market plays a major role in the transmission of shocks (Li, 2007).

6.2. Variance-Covariance Equation Analysis

Panel B of Table 2 reports the estimated coefficients of the variance-covariance system.

6.2.1. Volatility Persistence

The sum of the GARCH coefficients, i.e., $(\phi_{11} + \phi_{12})$ and $(\phi_{22} + \phi_{21})$, measures volatility persistence (see Li, 2007; Li & Majerowska, 2008) for the first market (Pakistan) and the second market (the US, India or Japan). In the Pakistan-US case, the volatility persistence of the Pakistani and US markets is 0.881 and 0.973 respectively. Similarly, the volatility persistence of the Pakistan-India and Pakistan-Japan pairs is 0.8911 and 0.9103, and 0.8845 and 0.9566, respectively. It is slightly lower for Pakistan than for the second market in each case, indicating that the Pakistani stock price index derives less of its volatility persistence from past volatility than from global markets (the US) or regional markets (India and Japan). Therefore, past

[3] www.worldbank.org

shocks play a greater role in the volatility of the Pakistani market stock index than the other global and regional markets we have considered.

6.2.2. Volatility Spillovers

The cross-market volatility spillover in terms of the ARCH and GARCH effects is captured by the off-diagonal parameters θ_{12} and θ_{21} of ARCH matrix Θ and by ϕ_{12} and ϕ_{21} of GARCH matrix Φ. The hypotheses associated with volatility spillovers are tested and reported in panel C of Table 3. The overall test of hypothesis H05 – no ARCH and GARCH volatility spillover between local markets and regional and global markets – is rejected for all country pairs except for Pakistan-Japan.

Focusing on the direction of spillover, we test hypothesis H06 of no volatility spillover from the second market (the US, India or Japan) to the Pakistani market. We reject this hypothesis for the pairs related to the US and Japan. The neighboring Indian market does not seem to have an impact on the volatility of the Pakistani market. The Pakistani market's volatility is also driven by global forces since the statistical significance of the US pair is very strong. Interestingly, we are unable to reject H07 with respect to the volatility spillover from Pakistan to India. Thus, while the Indian market leads in terms of its impact on Pakistani stock returns, it is the Pakistani market's volatility that is found to influence that of the Indian market. The Pakistani market, therefore, has a volatility spillover toward all the markets considered except for Japan.

Hypotheses H08 to H13 test the nature of volatility shocks, i.e., whether they include a past volatility component (the GARCH component) or the squared shock of the past day (the ARCH component). Generally, the results show that unanticipated shocks (ARCH shocks) are more important in driving volatility spillover, as they are significant for all the pairs. Barring Japan, there seems to be bidirectional causality between the local Pakistani market and the regional and global markets. However, the GARCH spillover effects – from the regional and global markets to the Pakistani market – are also significant.

Hypotheses H14 to H16 test whether the impact of local anticipated and unanticipated past-day shocks is asymmetric, i.e., whether shocks related to bad news have more impact on current volatility than shocks associated with good news. The asymmetric elements d_{12} and d_{21} of matrix D in variance-covariance equation (3) capture the cross-market asymmetric effect. The results are interesting: Pakistani market volatility is related to the regional emerging market of India (H14). Bad-news events such as the 2008 Mumbai terrorist attacks are likely to have a much stronger effect on Pakistani volatility than good news from the Indian market. Its volatility appears to increase more in response to shocks associated with bad news from Pakistan than good news. Such asymmetric volatility responses do not emerge with respect to the developed markets of the US and Japan.

Our results reveal two important and related findings. First, the Pakistani market seems to operate more or less exogenously, as it receives smaller shocks from overseas markets relative to own local shocks. Earlier studies such as Aggarwal, Inclan and Leal (1999) and Rouwenhorst (1995) show that local factors are more important than global factors in affecting emerging market returns. In our case, such findings are manifested more in terms of volatility than returns per se since local shocks are associated with a much larger increase in volatility than shocks originating from the regional and global markets.

6.2.3. Multivariate Spillovers

Table 4 gives the estimated results for the multivariate asymmetric VARMA(1,1)-GARCH(1,1) models with BEKK specifications for two sets of markets – Pakistan-India-US and Pakistan-India-Japan – using a multivariate student t-distribution of errors. Panels A and B of the table give the AR, MA, ARCH and GARCH estimates and the asymmetric coefficient matrices, respectively. Panel C reports the diagnostics of the estimated models. The multivariate Ljung–Box Q statistics for the third and sixth orders of the squared standardized residuals show that there is no serial dependence in the latter, indicating the appropriateness of the fitted variance-covariance equations for all two sets. The subscripts $i = 1$ and $i = 2$ denote the Pakistani and Indian markets, respectively, while $i = 3$ denotes the third market, i.e., the US or Japan.

Table 4: Estimated coefficients for multivariate asymmetric GARCH model and its diagnostics

Parameter	VARMA(1,1)-BEKK(1,1)					
	Pakistan-India-US			Pakistan-India-Japan		
	Pakistan (i = 1)	India (i = 2)	US (i = 3)	Pakistan (i = 1)	India (i = 2)	Japan (i = 3)
Panel A: Estimated coefficients of mean equations						
λ_i	0.020***	0.122***	0.012	0.008	0.045	0.016
ψ_{1i}	0.962*	-0.122***	-0.407	0.956*	-0.082	-0.001
ψ_{2i}	0.662	-0.305	-3.029**	0.671***	-0.098	-0.202
ψ_{3i}	-0.034	0.001	0.486**	0.715***	-0.738**	0.376**
ω_{1i}	-0.929*	0.140***	0.472	-0.921*	0.098	0.010
ω_{2i}	-0.663	0.349	3.520**	-0.635***	0.174	0.206
ω_{3i}	0.035	0.007	-0.545**	-0.682***	0.858**	-0.450**
Panel B: Estimated coefficients of variance and covariance equations						
θ_{1i}	0.371*	-0.065	-0.010	0.337*	-0.086**	-0.019
θ_{2i}	-0.011	0.090*	-0.012**	-0.007	-0.103*	-0.078*
θ_{3i}	0.073*	0.235*	-0.089*	-0.023*	-0.005	0.095*
ϕ_{1i}	0.892*	-0.014	0.001	0.892*	-0.010	-0.003
ϕ_{2i}	-0.001	0.926*	-0.002	0.003	0.930*	-0.019*
ϕ_{3i}	0.017**	0.018	0.963*	-0.002	-0.021*	0.969*
d_{1i}	0.290*	0.161*	-0.003	0.349*	0.112**	-0.034
d_{2i}	-0.005	0.401*	0.001	-0.019***	0.410*	0.051**
d_{3i}	-0.025	-0.021	0.318*	0.012	0.040	0.258*
Panel C: Diagnostics						
LB(3)	23.689 (0.647)			19.874 (0.835)		
LB(6)	46.304 (0.762)			40.609 (0.911)		
LB2(3)	22.922 (0.689)			26.852 (0.471)		
LB2(6)	42.026 (0.881)			45.422 (0.790)		
Log likelihood	-10,123.539			-13,459.982		
AIC	20,357.079			27,029.964		
BIC	20,689.480			27,362.366		

*, **, *** = significant at 1, 5 and 10 percent, respectively. P-values given in parentheses.
LB and LB2 = multivariate Ljung-Box (portmanteau test) statistics for standardized and squared standardized residuals, respectively.
Source: Authors' estimates.

Table 5 gives the Wald test results for the joint restrictions of the MGARCH model fitted for two sets – Pakistan-India-US and Pakistan-India-Japan. The significance of hypothesis H17 in both MGARCH cases indicates the influence of the regional and global markets on the mean, variance and asymmetric effects of the Pakistani market. The rejection of hypotheses H18, H19 and H20 indicates joint significant cross-mean and variance spillovers and a cross-market asymmetric effect on Pakistan from either the regional markets (India and Japan) or the global market (the US). While these joint multivariate tests point to the general impact of the regional and global markets on the Pakistani market, the bivariate GARCH results are more indicative of the specific country and the extent of its influence over the Pakistani market.

Table 5: Wald test for restrictions on multivariate asymmetric GARCH model

Hypothesis	Country groups	
	Pakistan-India-US	**Pakistan-India-Japan**
H017: No joint spillover in mean or variance and cross-market asymmetric effect on Pakistani stock market		
$\psi_{12} = \psi_{13} = \omega_{12} = \omega_{13} = \theta_{12} = \phi_{12} = \theta_{13} = \phi_{13} = d_{12} = d_{13} = 0$	51.769*	39.271*
	(0.000)	(0.000)
H18: No joint mean spillover from regional and global stock markets to Pakistani stock market		
$\psi_{12} = \psi_{13} = \omega_{12} = \omega_{13} = 0$	37.491*	23.490*
	(0.000)	(0.000)
H19: No joint volatility spillover from regional and global stock market to Pakistani stock market		
$\theta_{12} = \phi_{12} = \theta_{13} = \phi_{13} = 0$	8.516***	10.151**
	(0.074)	(0.037)
H20: No joint cross-market asymmetric response from regional and global stock market to Pakistani stock market		
$d_{12} = d_{13} = 0$	9.563*	6.698**
	(0.008)	(0.035)

Note: *, **, *** = significant at 1, 5 and 10 percent, respectively. P-values given in parentheses.
Source: Authors' estimates.

7. Conclusion

The objective of this article was to investigate the spillover returns and volatility shocks from regional and global markets to the Pakistani stock market. We estimate a bivariate asymmetric VARMA(1,1)-GARCH(1,1) model with BEKK specifications to capture the mean and variance spillover channels for the pairs Pakistan-US, Pakistan-India and Pakistan-Japan and the groups Pakistan-India-US and Pakistan-India-Japan. The hypotheses tested through the mean and variance equation parameters analyze the different transmission channels between the Pakistani market and the regional and global markets.

We find evidence of unidirectional regional and global returns spillover toward Pakistan. The mean return of the Pakistani stock market depends on past-day returns and unanticipated shocks emanating from the regional and global markets. Thus, the global and regional equity markets Granger-cause the Pakistani market. The US market has the largest mean spillover to the Pakistani market while the regional markets have lower spillovers. However, the magnitude of the own-market spillover for Pakistan is greater than the cross-market spillover. The results of the mean returns show that asset prices in Pakistan are affected by regional and global business conditions. Our findings support the 'global center' hypothesis, which implies that the US market plays a vital role in transmitting news to the emerging market of Pakistan.

Although the Pakistani market has a high degree of volatility persistence in all cases, its volatility persistence magnitude is lower than that of the other markets. This suggests that volatility persistence stemming from past volatility for the Pakistani market has a smaller proportional effect on its share prices relative to the effect other markets have on their share prices. Thus, the volatility of the Pakistani stock market is derived more from past shocks than from other global or regional markets (the US, India and Japan).

The US and Japanese markets have unidirectional volatility spillovers toward the Pakistani market while the latter has a unidirectional volatility spillover toward India. We find that own-market volatility spillover is significant for Pakistan and more important than global volatility shocks. The past volatility of the (developed) US and Japanese markets is a source of current volatility in Pakistan, while the regional emerging market of India transmits its impact on Pakistani market volatility through unanticipated idiosyncratic (squared) shocks. The volatility of the Pakistani market increases more in response to past-day bad news from India than to good news of the same magnitude.

We also find that the current volatility of the Pakistani market is influenced primarily by past-day shocks, past-day volatility and own asymmetric effects. Foreign markets have very limited influence on the current value of Pakistani market volatility. This is evident from the magnitude of the own versus cross-market effects. The results indicate that the global market (the US) has the highest magnitude of cross-mean and volatility spillovers to the Pakistani market. The MGARCH tests confirm the findings of the bivariate tests and indicate that the regional and global markets have a significant impact on the mean, volatility and asymmetric volatility of the Pakistani stock market.

The Pakistani stock market is integrated with the global US market and regional Asian markets to some degree, but the small magnitude of global and regional market shocks suggests that the Pakistani stock market operates more or less exogenously. The impact of overseas shocks, while statistically significant, is economically very small. This low level of linkages would imply that the expected returns on investment in Pakistani stock exchanges are determined mainly by the country's exposure to local country-specific risk factors.

The news related to overseas development is less important. This weak integration of the Pakistani market makes it more suitable for inclusion in internationally diversified portfolios. Since the volatility of the Pakistani market can be predicted to some extent by past-day global and regional market shocks, we can conclude that the Pakistani market is not semi-strong-form-efficient. Future research could focus on the nature of macroeconomic shocks and global financial crises with respect to the transmission of returns and volatility shocks to the local Pakistani market.

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Appendix

Expansion of bivariate asymmetric VARMA(1,1)-GARCH(1,1)-BEKK model

The mean equation is:

$$R_t = \Lambda + \Psi R_{t-1} + \Omega u_{t-1} + u_t \ , u_t | I_{t-1} \sim N(0, \Sigma_t)$$

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} + \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{bmatrix} \begin{bmatrix} u_{1,t-1} \\ u_{2,t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} + \begin{bmatrix} \psi_{11} r_{1,t-1} + \psi_{12} r_{2,t-1} \\ \psi_{21} r_{1,t-1} + \psi_{22} r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \omega_{11} u_{1,t-1} + \omega_{12} u_{2,t-1} \\ \omega_{21} u_{1,t-1} + \omega_{22} u_{2,t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \lambda_1 + \psi_{11} r_{1,t-1} + \psi_{12} r_{2,t-1} + \omega_{11} u_{1,t-1} + \omega_{12} u_{2,t-1} + u_{1,t} \\ \lambda_2 + \psi_{21} r_{1,t-1} + \psi_{22} r_{2,t-1} + \omega_{21} u_{1,t-1} + \omega_{22} u_{2,t-1} + u_{2,t} \end{bmatrix}$$

$$r_{1,t} = \lambda_1 + \psi_{11} r_{1,t-1} + \psi_{12} r_{2,t-1} + \omega_{11} u_{1,t-1} + \omega_{12} u_{2,t-1} + u_{1,t}$$

$$r_{2,t} = \lambda_2 + \psi_{21} r_{1,t-1} + \psi_{22} r_{2,t-1} + \omega_{21} u_{1,t-1} + \omega_{22} u_{2,t-1} + u_{2,t}$$

The variance-covariance equation is:

$$H_t = \Gamma'\Gamma + \Theta' u_{t-1} u'_{t-1} \Theta + \Phi' H_{t-1} \Phi + D' \xi_{t-1} \xi'_{t-1} D$$

where $\xi_{t-1} = u_{t-1}$ if $u_{t-1} < 0$, and 0 otherwise.

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & 0 \\ \gamma_{21} & \gamma_{22} \end{bmatrix}' \begin{bmatrix} \gamma_{11} & 0 \\ \gamma_{21} & \gamma_{22} \end{bmatrix} + \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix}' \begin{bmatrix} u_{1,t-1} \\ u_{2,t-1} \end{bmatrix} \begin{bmatrix} u_{1,t-1} & u_{2,t-1} \end{bmatrix} \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{21} \\ d_{12} & d_{22} \end{bmatrix}' \begin{bmatrix} \xi_{1,t-1} \\ \xi_{2,t-1} \end{bmatrix} \begin{bmatrix} \xi_{1,t-1} & \xi_{2,t-1} \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$$

$$= \begin{bmatrix} {\gamma_{11}}^2 + {\gamma_{21}}^2 & \gamma_{21}\gamma_{22} \\ \gamma_{21}\gamma_{22} & {\gamma_{22}}^2 \end{bmatrix} + \begin{bmatrix} \theta_{11} & \theta_{21} \\ \theta_{12} & \theta_{22} \end{bmatrix} \begin{bmatrix} {u^2}_{1,t-1} & u_{1,t-1}u_{2,t-1} \\ u_{1,t-1}u_{2,t-1} & {u^2}_{2,t-1} \end{bmatrix} \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} \phi_{11} & \phi_{21} \\ \phi_{12} & \phi_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} d_{11} & d_{21} \\ d_{12} & d_{22} \end{bmatrix} \begin{bmatrix} {\xi^2}_{1,t-1} & \xi_{1,t-1}\xi_{2,t-1} \\ \xi_{1,t-1}\xi_{2,t-1} & {\xi^2}_{2,t-1} \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$$

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An Empirical Assessment of the Q-Factor Model: Evidence from the Karachi Stock Exchange

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Abstract

This paper tests the validity of the q-factor model on stocks listed on the Karachi Stock Exchange in Pakistan. The q-factor model is an investment-based factor model that explains stock returns based on market, profitability, investment and size factors and it tends to outperform the traditional CAPM, the Fama and French (1993) three-factor model and Carhart (1997) four-factor model, with some exceptions. While the model has been tested using data from stock markets in developed countries, the dynamics of emerging stock markets are significantly different, warranting a reapplication of the model to average stock returns in a developing market. We use data from the Karachi Stock Exchange to test the model in an emerging market context. The results show that, as firms increase their investment, their stock returns decline. Hence, a firm's investment is conditional on a given level of profitability. The size effect is strongly significant for small firms, but absent for large firms. Finally, the study identifies new factors that give a better understanding of returns in the context of an emerging economy such as Pakistan.

Keywords: Asset pricing, q-factor model, Karachi Stock Exchange, stock return.

JEL classification: G11, G12.

1. Introduction

This study investigates which factors determine the returns on stocks listed on the Karachi Stock Exchange (KSE) by applying the q-factor model developed by Hou, Xue and Zhang (2012, 2015). The q-factor model is an investment-based factor model derived from Tobin's q theory, which explains several anomalies of average returns not explained by earlier asset pricing models. This study empirically tests the validity of the factors identified by the q-factor model – market, investment, profitability and size – in relation to stocks listed on the KSE.

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Hou et al. (2012, 2015) developed a q-factor model that explains several average-return anomalies, most significantly the momentum effect. The q-factor model explains the impact of a firm's investment behavior and profitability on expected average stock returns – factors not explained by the Fama and French (1993) three-factor model. The q-factor model derives the investment and profitability factors and their relation to expected returns from Tobin's q theory (Tobin, 1969), which states that the firm's investment decisions depend on the ratio of the market value of capital to the replacement cost of capital – termed the marginal q. Firms tend to invest more when the marginal q is high and less when it is low. Similarly, all else equal, a high cost of capital means low investment and a low cost of capital means high investment.

The model considers the combined effect of profitability and investment because the relationship between the firm's investment and stock returns is conditional on a certain level of profitability, as high-investment firms tend to have higher levels of profitability (Fama & French, 2006). Thus, for a given expected profitability for the firm, its expected returns will decrease with increasing investment; for a given level of investment, its expected returns will increase with increasing profitability. Similarly, the positive relationship between profitability and returns is conditional on a given level of investment, as profitability may also be associated with higher investment. Specifically, the q-factor model states that the expected returns of a portfolio are explained by its sensitivity to four factors: market excess returns, the difference between the returns on small and large capitalization stocks, the difference between the returns on low and high investment-to-asset (I/A) stocks and the difference between the returns on high and low return-on-equity (ROE) stocks.

The three-factor model does not explain high asset growth in stocks (see Fama & French, 1993). Acknowledging the new q-factor model presented by Hou et al. (2012), but using a different theoretical framework, Fama and French (2015) test a comprehensive five-factor model that incorporates the investment and profitability effects into their earlier three-factor model. They find that the five-factor model outperforms the latter. However, the value factor becomes redundant and the five-factor model fails to capture the low returns on small stocks that have invested more despite low profitability. Accordingly, they suggest dropping the value factor if the objective is to measure regression intercepts, but retaining all five factors if the portfolios possess size, value, profitability and investment premiums. Fama and French (2017) tested the five-factor model for a sample drawn from North America, Europe and Japan, which largely explained average returns, but with wide variability among factors across regions. The investment and profitability factors were strongest for North America, but insignificant for Japan and the Asia-Pacific region, where the value factor is strong.

Using data from the New York Stock Exchange, Hou, Xue and Zhang (2017) compared the performance of the q-factor model, the capital asset pricing model (CAPM), the Fama–French three-factor model, Carhart's (1997) four-factor model, Pástor and Stambaugh's (2003) model and Fama and French's (2015) five-factor model in explaining hundreds of stock return anomalies. They found that the two closely related investment-based models, the q-factor and five-factor models, outperform the others in explaining the maximum number of anomalies as well as expected returns. They termed the five-factor model a noisy version of the q-factor model. The q-factor model also explained the momentum effect identified by Jegadeesh and Titman (1993) better than other models, including that presented by Carhart et al. (1996), which also contains a momentum factor. While the q-factor model best captured the effect of momentum and profitability, the five-factor model explained value-versus-growth anomalies better than other models.

The q-factor model is a recent addition to the literature on asset pricing and there have been very few attempts to validate the model empirically. This study empirically tests the validity of the q-factor model based on the portfolio construction methodology developed by Fama and French (1993, 1996). Our sample consists of 100 companies listed on the KSE over the period June 2004 to May 2014. The objective is to determine the significance of the four factors identified by the q-factor model, i.e., market, size, investment and profitability. The study also estimates the explanatory power of excess market returns, small market capitalization (MC), a low I/A ratio and a high ROE ratio in KSE stock returns. This could help stock market investors determine whether one or more of the factors identified by the q-factor model can be used as a criterion for investment and portfolio formation. It will also help researchers and financial analysts better understand stock movements.

The next section discusses the relevant literature. Section 3 explains the theoretical framework. Section 4 describes the study's methodology and Section 5 discusses its findings. The article concludes with a set of policy implications, recommendations and limitations.

2. Theoretical Framework

The q-factor model generates hypotheses based on Tobin's q theory (see Tobin, 1969; Cochrane, 1991), while Fama and French (2015) derived their investment-based factor model from the dividend discount model presented by Gordon and Shapiro (1956).

2.1. *Tobin's Q Theory*

Tobin's (1969) theory of investment connects the financial market with the goods and services market. It suggests that the rate of investment is based on the ratio of the market value of a firm's capital to its replacement cost. Tobin's Q, also called average Q, is expressed as

$$Q = \frac{Market\ value\ of\ firm\ capital}{Replacement\ cost\ of\ capital} \quad (1)$$

Tobin's q theory provides certain guidelines for investment. The market value of the firm's capital is represented by the stock price. The firm's capital investment decision depends on where Q is in relation to 1. The theory states that firms should invest more capital when Q > 1 (which will bring it down to 1) and disinvest their capital stock when Q < 1 (which will raise it to 1). This means that capital has more value within the firm when Q > 1 and outside the firm when Q < 1. In a state of equilibrium, Q = 1 and there is no need for capital investment or disinvestment. However, an increase or decrease in capital is not free of cost. Tobin's q theory assumes that adjustment costs (such as installation costs) are associated with investment.

2.2. *Dividend Discount Model*

Hou et al. (2015) use the q theory of investment to derive their q-factor model. The model can also be estimated by applying the dividend discount model, following Fama and French (2015), according to which the worth of a stock is equal to the sum of all future dividends discounted to their present value (Gordon & Shapiro, 1956; Gordon, 1962). The model can be represented as follows:

$$P_0 = \frac{\sum_{n=1}^{\infty} E(d_t)}{(1+ke)^t} \quad (2)$$

where P_0 is the share price at time 0, $E(d_t)$ is the expected dividend per share at time *t* and *ke* is the internal rate of return. The dividend at time *t* can be expressed as the difference between total and retained earnings (the portion of earnings that is reinvested).

The present market value of the firm is represented as:

$$P_0 = \frac{\sum_{t=1}^{\infty} TE_t - RE_t}{(1+ke)^t} \tag{3}$$

where TE_t denotes total earnings at time t and RE_t denotes retained earnings at time t. Retained earnings can be further expressed as the difference between the book values of equity.

According to Miller and Modigliani (1961), the market value of a stock can be shown as follows:

$$P_0 = \frac{\sum_{t=1}^{\infty} \left(TE_t - (B_t - B_{t-1})\right)}{(1+ke)^t} \tag{4}$$

Here, $(B_t - B_{t-1})$ is the change in the book value of equity. The equation implies that higher earnings TE_t, reflected by profitability, will lead to higher expected returns, while higher growth in equity $(B_t - B_{t-1})$, i.e., higher investment, will lead to lower expected returns. We draw on the q-theory of investment as discussed above for our theoretical model.

3. Research Methodology

The four factors included in the q-factor model are market, size, investment and profitability. The market factor is derived from the CAPM. MC is used as a proxy for size, the I/A ratio as a proxy for investment and the ROE as a proxy for profitability. The study employs stock portfolios instead of individual stocks. Blume (1970) suggests that the motivation for creating stock portfolios is to reduce idiosyncratic risk, as the errors of individual stocks will offset each other if they are grouped in a portfolio. The three factors are constructed using the standard methodology developed by Fama and French (1993, 1996).

3.1. Data Source and Sample

The data was obtained from companies' financial statements, the KSE data portal and the State Bank of Pakistan's website over the sample period. The population consisted of all the stocks listed on the KSE during 2004–14. The number of listed companies in 2004 was 701, which dropped to 600 by 2014 (Securities and Exchange Commission of Pakistan, 2014). Thus, any companies that had been delisted for any reason were not included in the study. The population also excluded 11 nonfinancial company sectors whose earnings did not rely on capital investments, namely, banks, development finance institutions, microfinance banks, leasing companies, investment banks, mutual funds, *modarabas*, exchange companies, insurance companies, housing finance and venture capital (State Bank of Pakistan, 2015). Additionally, any stocks with negative book equity were omitted.

The sample, which represents about 25 percent of the population, consists of 100 stocks listed on the KSE for the period starting June 2004 and ending May 2014. According to Hair et al. (2010), the suggested ratio of observations to the number of predictors is 15 to 20. We have data from 100 companies and four predictors, giving us an observation-to-predictor ratio of 25 – well above the minimum requirement. The stocks were selected using simple random sampling. This was done by assigning a serial number to each firm and then randomly selecting 100 serial numbers. The nonfinancial sectors from which the data was collected are listed in Table 1.

Table 1: Sectors of nonfinancial companies listed on the KSE

Sector	Number of companies
Textiles	152
Sugar	31
Food	16
Chemicals, chemical products and pharmaceuticals	45
Manufacturing	32
Mineral products	8
Cement	20
Motor vehicles, trailers and auto parts	20
Fuel and energy	22
Information, communication and transport services	13
Coke and refined petroleum products	10
Paper, paperboard and products	9
Electrical machinery and apparatus	7
Other services activities	11

Source: State Bank of Pakistan (2015).

The unit of study is the portfolio (formed by combining a group of stocks). A portfolio comprises stocks with similar characteristics such as size, investment and profitability. The sample portfolios are dynamic and updated each year to maintain their specific characteristics. Thus, a stock whose characteristics have changed over the year can jump from one portfolio to another.

3.2. Excess Monthly Returns

We use a one-month horizon for the tests by taking the closing price on the last day of each month. The monthly stock returns are calculated by applying the formula given in equation (5):

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}} \tag{5}$$

where R_t is the stock return in the current month t, P_t is the closing price of stock i at the end of the current month t and P_{t-1} is the closing price of stock i at the end of the previous month $t-1$.

The benchmark KSE 100 index is taken as a proxy for the market portfolio. The monthly market returns are calculated by dividing the change in the KSE 100 over a month by its closing value for the previous month:

$$R_{mt} = \frac{(KSE_t - KSE_{t-1})}{KSE_{t-1}} \tag{6}$$

where R_{mt} is the return on the market portfolio in the current month t, KSE_t is the closing value of the KSE 100 at the end of the current month t and KSE_{t-1} is the closing value of the KSE 100 at the end of the previous month $t-1$.

The risk-free return is subtracted from the value-weighted return on the portfolio to obtain the excess return. The three-month T-bill rate is used as a proxy for the risk-free rate (see Harrington, 1987). Similarly, the excess market return is calculated by subtracting the risk-free return from the market return. The annualized three-month T-bill return is converted into a monthly return using the formula below:

$$Monthly\ return = (1 + annual\ return)^{\frac{1}{12}} - 1 \tag{7}$$

3.3. MC, ROE and I/A Ratio

The value of MC at the end of each year is obtained by multiplying the stock price by outstanding shares:

$$MC = share\ price \times outstanding\ shares$$

The current value of ROE is obtained by dividing net income by one-year-lagged book equity:

$$ROE_t = \frac{net\ income}{book\ equity_{t-1}} \tag{8}$$

The I/A ratio is calculated as the annual change in gross property, plant and equipment plus the annual change in inventory divided by the lagged book value of assets (see Chen, Novy-Marx & Zhang, 2011). The change in property, plant and equipment is taken as a standard measure of firm-level investment (Eberly, Rebelo & Vincent, 2008). The change in inventory captures investment in short-lived assets during an operating cycle:

$$\frac{I}{A} = \frac{(PPE_t - PPE_{t-1}) + (inv_t - inv_{t-1})}{Total\ assets_{t-1}} \tag{9}$$

3.4. Portfolio Formation

The percentile technique is used to sort the 100 stocks by size, investment and profitability. The portfolios are constructed by a triple two-by-three-by-three sorting of MC, the I/A ratio and ROE. For the size factor, the stocks are split into two groups by applying a breakpoint at the 50th percentile of the ranked values of MC. For the investment factor, the stocks are split into three groups, using breakpoints at the 30th and 70th percentiles of the ranked values of the I/A ratio. For the profitability factor, the stocks are split into three groups, using breakpoints at the 30th and 70th percentiles of the ranked values of ROE. Two MC, three I/A ratio and three ROE groups intersect to create 18 portfolios. Each portfolio is created by combining stocks whose MC, I/A ratio and ROE intersect with each other. These portfolios are presented in Table 2.

Table 2: Portfolios ranked by MC, I/A ratio and ROE

	ROE			**MC**
I/A	**1st tercile**	**2nd tercile**	**3rd tercile**	
1st tercile	P1	P3	P5	1st median
	P2	P4	P6	2nd median
2nd tercile	P7	P9	P11	1st median
	P8	P10	P12	2nd median
3rd tercile	P13	P15	P17	1st median
	P14	P16	P18	2nd median

Source: Authors' estimates.

Since it is possible for the sampled companies to change rankings due to changes in size, investment and profitability, we revise the ranking and sorting of stocks for every year in June. This allows stocks to move freely from one portfolio to another at the end of each year. The stocks are required to match the characteristics of the corresponding I/A ratio and ROE tercile or MC median only for the current year.

3.5. Value-Weighted Portfolio Returns

The weighted average monthly returns of each portfolio are calculated by assigning weights based on the MC of their constituent stocks. The large-capitalization stocks in each portfolio have greater weight than the smaller ones and thus contribute more to total portfolio returns.

3.6. Factor Construction

The stocks in the first ROE tercile (P1, P2, P7, P8, P13, P14) are low-profitability stocks and those in the third ROE tercile (P5, P6, P11, P12, P17, P18) are high-profitability stocks. The stocks in the first I/A tercile (P1, P2, P3, P4, P5, P6) are low-investment stocks and those in the third I/A tercile (P13, P14, P15, P16, P17, P18) are high-investment stocks. The stocks in the first MC median (P1, P3, P5, P7, P9, P11, P13, P15, P17) are small stocks and those in the second MC median (P2, P4, P6, P8, P10, P12, P14, P16, P18) are large stocks.

The size factor in the q-factor model is represented by MCSMB. MCSMB is constructed by subtracting the average returns of all nine small-capitalization portfolios from the average returns of all nine large-capitalization portfolios for each month. The subtraction represents taking a long position on small portfolios and a short position on large portfolios. The investment factor is represented by I/ALMH. I/ALMH is formulated by subtracting the average returns of all six high-I/A ratio portfolios from the average returns of all six low-I/A ratio portfolios for each month. Here, subtraction represents taking a long position on low-investment portfolios and a short position on high-investment portfolios. The profitability factor is represented by ROEHML. ROEHML is formulated by subtracting the average returns of all six low-ROE portfolios from the average returns of all six low-ROE portfolios for each month. Here, subtraction represents taking a long position on high-profitability portfolios and a short position on low-profitability portfolios.

3.7. Empirical Model

The q-factor model has the following multivariate linear expression:

$$E(R_p) - R_f = \beta_o + \beta_1(R_m - R_f) + \beta_2 MC_{SMB} + \beta_3 I/A_{LMH} + \beta_4 ROE_{HML} + \epsilon \qquad (10)$$

where $E(R_p)$ = expected return of portfolio p, R_f = monthly risk-free rate of return, $E(R_p) - R_f$ = monthly excess return on portfolio, $(R_m - R_f)$ = monthly excess market return, MC_{SMB} = long position on small portfolios and short position on large portfolios, I/A_{LMH} = long position on low-investment portfolios and short position on high-investment portfolios, and ROE_{HML} = long position on high-profitability portfolios and short position on low-profitability portfolios. β_1, β_2, β_3 and β_4 are the regression coefficients of the independent variables, β_0 is the intercept and ϵ is the error term.

The regression is applied to all 18 portfolios. The monthly excess portfolio returns are taken as the dependent variable. $(R_m - R_f)$, MC_{SMB}, I/A_{LMH} and ROE_{HML} are the independent variables. The 18 portfolios are also tested using the CAPM and the results compared with those for the q-factor model.

3.8. Hypotheses

The hypotheses we test are as follows:

- H_1: The excess returns of the portfolios are positively related to excess market returns.
- H_2: The excess returns of small-MC portfolios are positively related to MCSMB.
- H_3: The excess returns of low-I/A portfolios are positively related to I/ALMH.
- H_4: The excess returns of high-ROE portfolios are positively related to ROEHML.

4. Empirical Results

To test the validity of the q-factor model using data from the KSE 100, we estimate equation (10) for each of the 18 portfolios. This involves multiple regression analysis with robust standard errors, given that heteroskedasticity is observed in eight of the portfolios. The descriptive statistics in Table 3 show that the mean values of the average returns vary from 1.004 to 1.040 with a standard deviation of 0.07–0.136. The minimum return is 0.57 and the maximum is 1.95.

Table 3: Descriptive statistics

Portfolio	Obs.	Mean	SD	Min	Max
P1	120	1.031038	0.1056943	0.83888	1.51049
P2	120	1.019340	0.0875300	0.79465	1.22562
P3	120	1.025833	0.0963303	0.80818	1.38102
P4	120	1.020513	0.0871659	0.67345	1.28651
P5	120	1.015764	0.0894201	0.69221	1.26382
P6	120	1.014576	0.0896182	0.57560	1.42166
P7	120	1.005441	0.0799410	0.75066	1.24733
P8	120	1.011772	0.0902566	0.61363	1.25116
P9	120	1.017096	0.0731724	0.81726	1.21686
P10	120	1.014072	0.0776979	0.82504	1.32364
P11	120	1.032450	0.1124963	0.82307	1.78466
P12	120	1.022794	0.0744963	0.85264	1.27880
P13	120	1.019339	0.1118930	0.71383	1.49122
P14	120	1.004073	0.0867751	0.75049	1.25894
P15	120	1.021825	0.0860618	0.81543	1.32749
P16	120	1.017632	0.0856179	0.69147	1.24887
P17	120	1.019526	0.1000590	0.79966	1.42179
P18	120	1.041620	0.1359149	0.66342	1.95311

Source: Authors' estimates.

The results of these estimations are given in Tables 4, 5 and 6. The market factor (β_1) is positive and significant at 1 percent for all portfolios except P5. For all nine large portfolios, the market factor has the highest beta of all four factors being tested in the q-factor model. However, the average size factor (β_4) of the nine small portfolios is stronger than their average market factor. The average β_1 for the 18 portfolios is 0.8769. The highest β_1 is for portfolio P13 and the lowest β_1 for P9. There is no marked variation in the strength of market betas across the portfolios.

Table 4: Q-factor model estimations P1 to P6

	P1	P2	P3	P4	P5	P6
β_1	0.8798***	0.8934***	0.7039***	0.9881***	0.9652	0.9511***
	(0.102)	(0.078)	(0.097)	(0.07)	(0.07)	(0.052)
β_2	0.1433	0.2161*	0.2606*	0.0165	0.3759***	0.2295***
	(0.253)	(0.114)	(0.142)	(0.096)	(0.103)	(0.076)
β_3	-0.2158	-0.356***	-0.0811	-0.2029**	0.2130**	0.3382***
	(0.332)	(0.102)	(0.126)	(0.095)	(0.091)	(0.068)
β_4	1.3732***	0.2378***	1.2639***	0.1416	0.5266***	-0.2058**
	(0.307)	(0.127)	(0.158)	(0.111)	(0.114)	(0.085)
β_5	0.0137***	0.0059	0.00904	0.00511	-0.00442	-0.0048
	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)	(0.004)
F-value	33.43	39.34	24.12	55.06	59.39	131.03
(4, 115)	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
R^2	0.5056	0.5778	0.4562	0.6563	0.6738	0.8201
n	120	120	120	120	120	120

Note: Standard errors are given in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' estimates.

The investment factor (β_2) is significant for 13 out of 18 portfolios. The five portfolios with insignificant investment factors include two low-investment (P1, P4) and two medium-investment (P10, P12) portfolios. The average β_2 for the six low-investment portfolios is 0.207, while the average β_2 for the six high-investment portfolios is –0.793. The investment factor has the strongest positive value for the low-investment portfolio P5 and the strongest negative value for the high-investment portfolio P18. The results show that four of the six low-investment portfolios have positive coefficients and all six high-investment portfolios (P13, P14, P15, P16, P17, P18) have negative and significant (at 1 percent) coefficients. Thus, as the firm increases its investment, its expected stock returns fall.

The profitability factor (β_3) is significant for 13 out of 18 portfolios. The four portfolios for which the profitability factor is insignificant include two low-profitability (P1, P3) and two high-profitability (P15, P16) portfolios. The profitability factor is significant for all portfolios with medium profitability. The average β_3 for the six low-profitability portfolios is –0.0507 and for the six high-profitability portfolios is –0.0507. The coefficient is smallest for portfolio P13 and largest for the high-profitability portfolio P18. These findings are consistent with the model's predictions: low-profitability portfolios have a negative β_3 and high-profitability portfolios have a positive β_3, with some exceptions. Thus, as the firm's profitability increases, its expected stock returns also increase.

Table 5: Q-factor model estimations P7 to P12

	P8	P9	P10	P11	P12
β_1	0.9451***	0.6996***	0.7769***	0.9264***	0.7388***
	(0.118)	(0.073)	(0.077)	(0.097)	(0.062)
β_2	-0.4041***	-0.253***	0.1361	-0.3741*	0.0515
	(0.132)	(0.107)	(0.107)	(0.209)	(0.09)
β_3	-0.6064***	-0.2152**	-0.2752**	0.6264**	0.2489***
	(0.12)	(0.095)	(0.111)	(0.279)	(0.08)
β_4	-0.0673	0.6360***	-0.0561	1.5500***	-0.0432
	(0.133)	(0.118)	(0.164)	(0.283)	(0.1)
β_5	0.0012	0.00338	0.00169	0.00667	0.00591
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
F-value	27.97	25.71	29.86	24.44	49.57
(4, 115)	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
R^2	0.625	0.4721	0.5899	0.6225	0.6329
n	120	120	120	120	120

Note: Standard errors are given in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' estimates.

Table 6: Q-factor model estimations P13 to P18

	P13	P14	P15	P16	P17	P18
β_1	1.0098***	0.8412***	0.857***	0.8716***	0.976***	0.8258***
	(0.102)	(0.07)	(0.069)	(0.076)	(0.077)	(0.135)
β_2	-1.008***	-0.757***	-0.607***	-0.309***	-0.726***	-1.351***
	(0.18)	(0.083)	(0.101)	(0.007)	(0.113)	(0.269)
β_3	-0.859***	-0.628***	-0.0778	-0.1196	0.4585***	0.9224***
	(0.158)	(0.07)	(0.09)	(0.1)	(0.101)	(0.317)
β_4	1.1099***	-0.0757	1.076***	-0.1465	0.9995***	0.3738
	(0.17)	(0.107)	(0.112)	(0.124)	(0.125)	(0.32)
β_5	0.008	-0.0051	0.0045	0.0035	-0.0036	0.0174***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)
F-value	32.05	52.92	54.46	38.82	61.85	18.09
(4, 115)	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
R^2	0.6819	0.6157	0.6545	0.5745	0.6827	0.5742
n	120	120	120	120	120	120

Note: Standard errors are given in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' estimates.

The size factor is significant for 10 out of 18 portfolios. The size factor is significant for four of the five small portfolios and tends to be stronger than their market factors. The average β_4 for the small portfolios is 1.017 while the average β_4 for the nine large portfolios is 0.017. The largest size coefficient is for the small portfolio P11 and the smallest size coefficient is for the large portfolio P6. These findings confirm the model's predictions: small portfolios have a strong, positive β_4 and large portfolios have an insignificant or negative β_4. Thus, as the firm's size increases, its expected stock returns decrease.

In a perfect asset-pricing model explaining excess returns above the risk-free rate, the value of the intercept must be close to 0 (Black, Jensen & Scholes, 1972). A zero-intercept is based on the risk-return relationship according to which there should be no return on taking no risk. A non-zero intercept indicates the model's failure to explain excess returns. The same rationale is extended to the q-factor model such that the intercept value is expected to be 0. The results show that the intercept values for all the portfolios are close to 0. This implies that the model is specified correctly (see Hou et al., 2017) and that it explains excess returns without needing additional variables.

The F-test for all 18 regressions is significant, with a p-value of 0.000. The average R-squared for all portfolios is 0.61. The highest R-squared is 0.82 for portfolio P6 and the smallest is 0.45 for portfolio P3. The R-squared values lie in a similar range for all groups of portfolios ranked by investment, size and profitability. The data used for these estimations is also used to estimate a CAPM, the results of which are significant for all 18 portfolios (Table 7). The F-test for each regression is significant, with a p-value of 0.000. The average R-squared for all portfolios is 0.38. Overall, the q-factor model has greater explanatory power than the CAPM.

Table 7: CAPM regression analysis

Portfolio	Intercept	p-value	β	p-value	R2	F test	p-value
P1	0.01773	0.048	0.5912	0.000	0.172	24.42	0.000
P2	0.00384	0.508	0.8306	0.000	0.490	113.40	0.000
P3	0.01368	0.102	0.4658	0.000	0.128	17.34	0.000
P4	0.00402	0.411	0.9388	0.000	0.633	203.80	0.000
P5	-0.00058	0.914	0.9235	0.000	0.580	162.80	0.000
P6	-0.00298	0.467	1.0564	0.000	0.757	367.70	0.000
P7	-0.00821	0.175	0.6307	0.000	0.339	60.56	0.000
P8	-0.00386	0.522	0.8466	0.000	0.480	108.90	0.000
P9	0.00447	0.441	0.5168	0.000	0.271	43.82	0.000
P10	-0.00090	0.853	0.7740	0.000	0.541	139.20	0.000
P11	0.01875	0.049	0.6341	0.000	0.174	24.91	0.000
P12	0.00775	0.078	0.7807	0.000	0.600	176.90	0.000
P13	0.00620	0.518	0.5730	0.000	0.144	19.77	0.000
P14	-0.01023	0.115	0.7016	0.000	0.356	65.17	0.000
P15	0.00882	0.209	0.5583	0.000	0.230	35.21	0.000
P16	0.00193	0.719	0.8532	0.000	0.542	139.60	0.000
P17	0.00487	0.532	0.7382	0.000	0.296	49.71	0.000
P18	0.02736	0.020	0.6950	0.000	0.143	19.70	0.000

Source: Authors' estimates.

Post-estimation, we test for multicollinearity using the variance inflation factor test. No multicollinearity is observed in the model (see Table A1 in the Appendix). The Breusch–Godfrey LM test results show that there is no autocorrelation at the first lag. Campbell et al. (2001) divide stock volatility into three components – market, industry and idiosyncratic, all of which exhibit time variation. The Breusch–Pagan test is carried out to test for heteroskedasticity, which emerges in eight out of 18 portfolios (see Table A2 in the Appendix). To remove the impact of heteroskedasticity on the estimators, we carry out the regressions with robust standard errors.

5. Discussion

This empirical study applies the q-factor model to a sample of stocks listed on the KSE by analyzing data from 100 companies for the period June 2004 to May 2014. The analysis involves running regressions on 18 portfolios with distinct characteristics. The average R-squared for all portfolios using the q-factor model is 0.61, while that for all portfolios using the CAPM is 0.38. This implies that the q-factor model vastly outperforms the CAPM. Since the intercept of the q-factor model is close to 0, we can assume the model is accurately specified.

The q-factor model consists of four factors: market, investment, profitability and size. The effect of the market factor on expected returns is positive and significant for all portfolios except one (P5). The effect of the investment factor on expected returns is significant for 13 out of 18 portfolios. It has a negative and significant effect for all six high-investment portfolios. The results show that, when the firm's level of investment is low, the effect of investment on expected market returns is insignificant or positive. However, as the firm increases its investment, expected returns decline.

The ideal portfolio according to the q-factor model is P6, which features small, low-investment, high-profitability stocks. All its factors are significant and consistent with the model's predictions (positive investment, profitability and size factors). Conversely, the worst portfolio according to the q-factor model is P14, which comprises large, high-investment, low-profitability stocks. Its investment and profitability factors have negative coefficients, while the size factor is insignificant. Overall, the q-factor model accurately forecasts the returns on stock portfolios with varying characteristics, while these results confirm the negative-investment-and-expected-return relationship.

The profitability factor is significant for 13 out of 18 portfolios. The low-profitability portfolios have negative coefficients and the high-profitability portfolios have positive coefficients. This means that low-profitability portfolios have a negative effect on expected returns, whereas an increase in profitability has a positive effect on expected returns for firms with high profitability. This implies there is a positive relationship between profitability and expected returns – a finding consistent with Fama and French (2015) and Hou et al. (2015, 2017). The size factor is significant for 10 out of 18 portfolios. It is insignificant for seven out of nine large portfolios, but positive for all nine small portfolios – in which size is the strongest of all four factors. The market factor is positive and significant at 1 percent for all portfolios except P5. For all nine large portfolios, the market factor has the highest betas of all four factors being tested in the q-factor model.

Studies using q-factor or similar models have been carried out for different countries/stock markets. Using weighted portfolios, Chen et al. (2011) investigate which factors explain the variations in a cross-section of expected returns on stocks listed on the NYSE, AMEX and NASDAQ. They find that investment and profitability explain most of the anomalies observed, including momentum, accruals, net stock issues and asset growth. They term this model the 'alternative' three-factor model and show that it yields significantly better results than the Fama–French three-factor model for stocks in the US.

Ammann, Odonia and Oesch (2012) evaluate the performance of an investment-based factor model by employing the I/A ratio and ROE for a sample of European stock markets (Austria, Belgium, Finland, France, Germany, Italy, Ireland, the Netherlands, Portugal and Spain) over 1990–2006. They find that the investment-based model performs better than the CAPM or Fama–French three-factor model in explaining asset return anomalies such as asset growth, short-term prior returns, net stock issues, total accruals and value effects. Fan and Yu (2013) investigate the momentum anomaly otherwise not explainable by the CAPM and Fama–French three-factor model. They use the investment-based alternative three-factor model and find that it explains the momentum anomaly in 12 out of 13 G-12 country stock markets and yields significantly lower intercept values.

Fama and French (2015) add the investment and profitability factors derived from the q theory of investment to their earlier three-factor model to form a comprehensive five-factor model directed at capturing the impact of size, value, profitability and investment. They find that it outperforms the earlier model. Their results also indicate that small high-investment stocks have lower returns than high-investment, low-profitability stocks. However, the value factor becomes redundant in the presence of the other four factors, especially investment and profitability.

Finally, Walkshäusl and Lobe (2014) test the q theory-based model, which employs investment and profitability, and the Fama–French three-factor model for a global portfolio of 40 non-US markets in emerging and developed countries. They conclude that the q theory-based model outperforms the three-factor model in capturing the momentum anomaly, but has less explanatory power in relation to average returns. This could mean that the investment-based model is sample-specific.

6. Conclusion

This study contributes to the literature by validating the factors identified in the q-factor model as predictors of the expected returns on investments in the KSE. This implies that the four factors taken up in the q-factor model are useful predictors of average returns not only in developed markets, but also in developing markets. The model adds investment and profitability as predictors of expected market returns in factor-based asset pricing.

Our results are largely in accordance with the q theory and other findings relevant to US and other markets, where all the factors are found to be significant (see Hou et al., 2015, 2017). In a study on the Vietnamese stock market, however, Nguyen, Ulku and Zhang (2015) show that profitability and investment are important determinants of asset returns, along with size and value. The Vietnamese stock market is distinct from other stock markets in that the state owns a large volume of stocks.

Of the two new factors identified in the q-factor model, profitability (measured by ROE) has been traditionally used in fundamental analysis. However, our results show that investment, represented by the I/A ratio, can also be used as a tool of fundamental analysis for individual stocks. Further, investors can trade against the investment and profitability factors to increase their returns. Finally, the q-factor model has better explanatory power than the traditional CAPM and can be used to explain various anomalies, allowing better portfolio valuation.

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Appendix

Table A1: Vector inflation factors of variables

Variable	VIF	1/VIF
Market factor	1.17	0.855147
Size factor	1.16	0.865533
Profitability factor	1.08	0.928310
Investment factor	1.08	0.928425
Mean VIF	1.12	

Source: Authors' estimates.

Table A2: Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

Portfolio	chi2(1)	Prob. > chi2	Portfolio	chi2(1)	Prob. > chi2
P1	8.77	0.0031*	P10	6.44	0.0111*
P2	0.67	0.4134	P11	66.96	0.0000*
P3	3.01	0.0829	P12	1.44	0.2308
P4	17.44	0.0000*	P13	7.06	0.0079*
P5	1.36	0.2441	P14	5.94	0.0148*
P6	1.56	0.2121	P15	2.95	0.0859
P7	0.04	0.8326	P16	2.04	0.1535
P8	12.28	0.0005*	P17	1.67	0.1959
P9	0.80	0.3726	P18	51.32	0.0000*

Note: * Heteroscedasticity is present.
Source: Authors' estimates.

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Poverty in Pakistan: A Region-Specific Analysis

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Abstract

Most of the earlier literature on poverty in Pakistan uses a single poverty line for the whole country or, at most, relies on a rural-urban divide. This segmentation fails to incorporate differences across provinces. This study estimates different poverty lines for the rural and urban segments of each province and region. Its estimated food, nonfood and overall poverty lines show that, with the exception of the capital territory of Islamabad, the urban poverty line is higher in all regions. The estimates of poverty show that, with the exception of Islamabad Capital Territory, rural poverty is much higher than urban poverty in all regions. We find that 25 percent of urban households and nearly 37 percent of rural households fall below the poverty lines we have defined. The study also finds that poverty measured in terms of households ignores household size and thus suppresses poverty figures.

Keywords: Poverty, income distribution, welfare, Pakistan.

JEL classification: I30, O15.

1. Introduction

Income distribution has always been of great interest to economists and any growth policy that worsens the distribution of income is self-defeating.[1] In the context of income distribution, the most deprived segment of society is the income group that lies below the poverty line. The poverty line is defined as a benchmark of the subsistence level: those households that lie below the poverty line are considered 'poor'.

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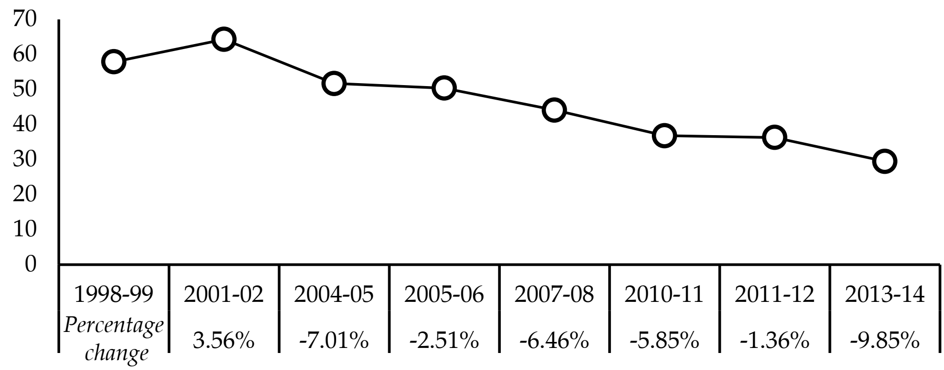
[1] A large volume of literature shows that the relationship between inequality and growth is debatable. For example, Neves and Silva (2014) present a comprehensive overview of such studies and conclude that this relationship is not the same for all countries and all periods, given their different circumstances. However, they find that a persistent increase in inequality over a long period hampers economic growth. On the comparison of rich and poor countries, studies such as Forbes (2000), Halter, Oechslin and Zweimüller (2014) and Castelló-Climent (2010) conclude that inequality adversely affects growth in poor countries, but has a positive impact in rich countries.

Poverty remains a central problem in developing countries and especially in Pakistan, where a significant proportion of the population lives below the poverty line. The official estimates of poverty in Pakistan are presented in Figure 1.[2] From 2001/02 to 2013/14, poverty declined continuously at an average annual rate of 2.9 percentage points. In 2013, 29.5 percent of the population lived below the poverty line. Put another way, 58 out of every 200 persons were poor and unable to meet their basic requirements.

Figure 1: Trends in poverty in Pakistan



Source: Pakistan Economic Survey, 2015-16.

Clearly, Pakistan must do more to alleviate poverty. More interestingly, the figure of 29.5 percent does not apply equally to all parts of Pakistan: there are large regional disparities. For instance, a rural-urban comparison of poverty reveals that the incidence of poverty is higher in rural areas (see, for example, Anwar & Qureshi, 2002; Jamal, 2005; Anwar, 2010). The differential within rural and urban areas is also more pronounced across the provinces (Ashraf, 2013).

Since Naseem's (1973) seminal work on poverty in Pakistan, numerous studies have conducted empirical analyses of Pakistani poverty. Most of these have used a single poverty line for the whole country or, at most, relied on a rural-urban divide (see Qureshi & Arif, 2001; Jamal, 2002, 2005; Jan, Chishti & Eberle, 2008). This segmentation fails to incorporate differences across provinces. The present study attempts to bridge the gap

[2] In 2013/14, the Government of Pakistan revised its methodology for estimating the poverty line and adopted a cost-of-basic-needs approach. The reference group covered households in the second, third and fourth deciles. The headcount indices for previous years were estimated by back-casting this poverty (for details, see Pakistan, Ministry of Finance, 2016).

in the literature by estimating region/province-specific poverty lines. It also estimates different poverty lines for the rural and urban segments of each province and the capital territory of Islamabad. These poverty lines are then used to measure the extent and depth of poverty in each region. The exercise should yield a deeper insight into poverty in Pakistan.

Analyzing poverty with region-specific poverty lines not only gives us more reliable estimates of poverty, but it also helps us understand the dynamics of poverty and thus formulate better policies to alleviate poverty in different regions. Mogstad, Langørgen and Aaberge (2007) also point out that country-specific poverty lines, which neglect regional price differences and assume uniform consumption habits across regions, are more likely to be biased.

The present study uses the latest data from the Household Integrated Economic Survey (HIES) for 2013/14. The HIES is conducted regularly by the Pakistan Bureau of Statistics and contains comprehensive information on income and expenditures at the household level. The HIES for 2013/14 consists of 17,989 households with representation from all the provinces and the federal capital territory.

The study is divided into five sections. Section 2 reviews earlier work on the estimation of poverty lines and measurement of poverty in Pakistan. Section 3 discusses the analytical framework and methodological issues related to estimating poverty lines and measuring poverty. The article's results are given in Section 4 and its conclusion in Section 5.

2. Literature Review

Among the numerous contributors to the large body of literature on poverty lines in Pakistan are Naseem (1973) and Alaudin (1975). Although the poverty lines they propose are arbitrary, this was an important step at the time and helped ascertain a standard of poverty measurement despite the use of less scientific research methodologies. Following in their footsteps, De Kruijk and Van Leeuwen (1985), Zaidi (1992) and others have specified relatively arbitrary poverty lines either in terms of expenditure or income for rural and urban areas of Pakistan.

Naseem (1977) arrives at a more scientific approach, the calorie intake approach, which offers relatively more realistic poverty line figures. However, his approach focuses on nutritional needs alone and assumes that households that can barely meet their nutritional requirements also consume nonfood items, or else they would have increased their calorie intake. Irfan and Amjad (1984), Ahmad (1998), and others also adopt this approach. Table 1 gives a comprehensive summary of earlier studies conducted on the estimation of poverty lines in Pakistan.

Table 1: Summary of poverty lines proposed/estimated by different studies in Pakistan

Approach/study	Unit of analysis	Region	Period of analysis
Arbitrary benchmarks			
Naseem (1973)	Per capita	Rural and urban Pakistan	1963/64, 1966/67, 1968/69, 1969/70
Alaudin (1975)	Per capita	Rural and urban Pakistan	1963/64, 1966/67, 1968/69, 1969/70
De Kruijk and Van Leeuwen (1985)	Household	Rural and urban Pakistan	1969/70, 1979
Ahmad and Ludlow (1989)	Per capita	Rural and urban Pakistan	1976/77, 1979, 1984/85
Zaidi (1992)	Adult equivalents	Overall Pakistan	1984/85
Zaidi and De Vos (1993)	Adult equivalents	Overall Pakistan	1987/88
Anwar (2005)	Per capita	Rural and urban Pakistan	2001/02
Calorie intake			
Naseem (1977)	Per capita	Rural and urban Pakistan	1963/64, 1966/67, 1968/69, 1969/70, 1970/71, 1971/72
Irfan and Amjad (1984)	Adult equivalents	Rural and urban Pakistan	1963/64, 1966/67, 1969/70, 1978/79
Ercelawn (1990)	Adult equivalents	Rural and urban areas of each province	1984/85
Mahmood et al. (1991)	Adult equivalents	Rural and urban Pakistan	1984/85
Jamal (2002)	Per capita	Rural and urban Pakistan	1987/88, 1996/97, 1998/99
Anwar (2006)	Adult equivalents	Overall Pakistan	2001/02
Jamal (2005)	Per capita	Rural and urban Pakistan	2001/02
Jan et al. (2008)	Adult equivalents	Overall Pakistan	2001/02
Basic needs			
Malik (1988)	Per capita	Rural and urban Pakistan	1963/64, 1966/67, 1969/70, 1979, 1984/85
Havinga et al. (1989)	Adult equivalents	Rural and urban Pakistan	1984/85

Approach/study	Unit of analysis	Region	Period of analysis
Jafri and Khattak (1995)	Per capita	Rural and urban Pakistan	1979 to 1990/91
Ali (1995)	Per capita	Overall Pakistan	1990/91
Ahmad (1998)	Adult equivalents	Rural and urban areas of each province	1992/93, 1993/94, 1995/96
Qureshi and Arif (2001)	Per capita	Rural and urban Pakistan	1998/99
Ashraf (2013)	Adult equivalents	Rural and urban areas of each province	2010/11
Pakistan, Ministry of Finance (2016)*	Adult equivalents	Overall Pakistan	2013/14

Note: * = new methodology based on reduced reference group.

As discussed above, the calorie intake approach overlooks other nonfood essentials. Thus, embedding nonfood needs into calorie intakes gives us the more scientific basic needs approach, which yields relatively comprehensive data on poverty lines. Malik (1988), Jafri and Khattak (1995), and Qureshi and Arif (2001) use this approach to establish a threshold for measuring poverty lines. In the earlier literature, the unit of analysis was normally per capita or adult equivalent. The per capita measure assigns an equal weight to all household members irrespective of their age and gender. The adult equivalent measure, on the other hand, incorporates age and gender and is thus considered more realistic.

The overview above reveals that most earlier studies have focused merely on the rural-urban divide: very few have tried to estimate poverty lines with provincial distinctions. In this regard, the present study attempts to estimate ten region-specific poverty lines for the rural and urban segments of each province and the capital territory of Islamabad.

3. Methodological Issues and Analytical Framework

This section examines the methodological issues associated with estimating poverty lines and measuring poverty.

3.1. Unit of Wellbeing

The first step concerns the selection of an indicator of economic wellbeing, with income and expenditure being our two main choices. We consider expenditure, as it is more relevant to poverty analysis. The consumption expenditures reported in the HIES enable us to calculate food and nonfood poverty lines separately.[3] Household expenditure, as defined by the HIES, refers to all money expenditure by the household or by its individual members on goods intended for consumption and on services. Also included is the value of goods and services received in kind and consumed, or self-produced and consumed by the household. Household consumption expenditure is calculated by taking the sum of the following yearly expenditure components:

- Expenditure on food items
- Value of self-produced, self-consumed food items
- Expenditure on nondurable goods and services
- Value of self-produced, self-consumed nondurable goods and services
- Consumption expenditure on durable goods and services
- Value of self-produced, self-consumed durable goods and services
- Value of in-kind consumed wages and salaries

3.2. *Unit of Analysis*

There are two main units of analysis. The first is per capita consumption, which treats all individuals equally. This kind of analysis may be misleading because nutritional requirements often vary with age and gender. A better approach is that of adult equivalence in which each individual is expressed as a fraction of an adult male.[4] Following Qureshi and Arif (2001), Arshad and Idrees (2008) and Mahmood and Idrees (2010), we use a calorie intake requirement chart to calculate adult-equivalents (see Table A1 in the Appendix).

3.3. *Defining the Poverty Line*

The present study estimates an absolute poverty line indicating the minimum acceptable living conditions, based on nutritional and other

[3] The Pakistan Bureau of Statistics ensures the reliability of HIES data through three-stage verification. At the first stage, the enumerator's work is certified by a field supervisor. At the second stage, the consistency of the data is analyzed by field staff at a regional field office. At the final stage, teams at the headquarters thoroughly review and edit the questionnaire to check for inconsistency or omissions. In case the questionnaire requires further clarification or has not been properly filled, the household is revisited to maintain the quality of the data (for details, see http://www.pbs.gov.pk/sites/default/files/pslm/publications/hies2013_14/HIES_2013-14_18_03_2015.pdf).

[4] For a detailed discussion of the unit of analysis, see Mahmood and Idrees (2010).

basic (nonfood) requirements.[5] This is known as the basic needs approach, an advantage of which is that it considers both food and nonfood needs. Numerous studies, including Malik (1988), Havinga et al. (1989) and Qureshi and Arif (2001) use this approach to estimate the poverty line. The poverty line thus comprises a food poverty line and nonfood poverty line. We estimate food poverty as the estimated cost of food consistent with the minimum required calorie intake for an adult equivalent. Following Greer and Thorbecke (1986), Ahmed (1991), Ercelawn (1991) and Qureshi and Arif (2001), the given calorie cost function is estimated to determine the food poverty line:

$$\ln X = a + bC + u$$

where X is the expenditure on the food basket consumed by an individual, C is the number of calories that an individual derives from this food basket and u is the error term.

Basic needs also include nonfood needs such as shelter, clothing and healthcare. In this respect, the simplest approach is to consider the 10 percent of households whose food expenditures lie between 95 and 105 percent of the food poverty line, and then calculate the weighted average of their nonfood expenditures to obtain a nonfood poverty line. The weighting scheme is as follows: 99–101 percent is given a weight of 5/15, 98–99 percent and 101–102 percent are given a weight of 4/15, 97–98 percent and 102–103 percent are given a weight of 3/15, 96–97 percent and 103–104 percent are given a weight of 2/15. Finally, 95–96 percent and 104–105 percent are given a weight of 1/15 (Ravallion, 1994, 1998).[6]

This method of calculating the nonfood component has been used by many studies, including White and Masset (2003) and Qureshi and Arif (2001). The rationale for this approach is that households on the edge of the food poverty line spend only on essential nonfood items. Thus, such expenditures can be considered the minimum nonfood items needed to escape poverty. The HIES (2013/14) data also supports this argument. We

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[5] Relative poverty defines the poverty line in relation to the average standard of living enjoyed by society (Kakwani, 2001) and thus does not take into account minimum living standards. Rather, it considers those individuals whose living standards are low relative to the rest of society. The subjective poverty line is based on the individual's preferences concerning a minimum income or expenditure. Of these three approaches, the absolute poverty line is considered the best as it calculates the minimum consumption expenditure needed to escape poverty.

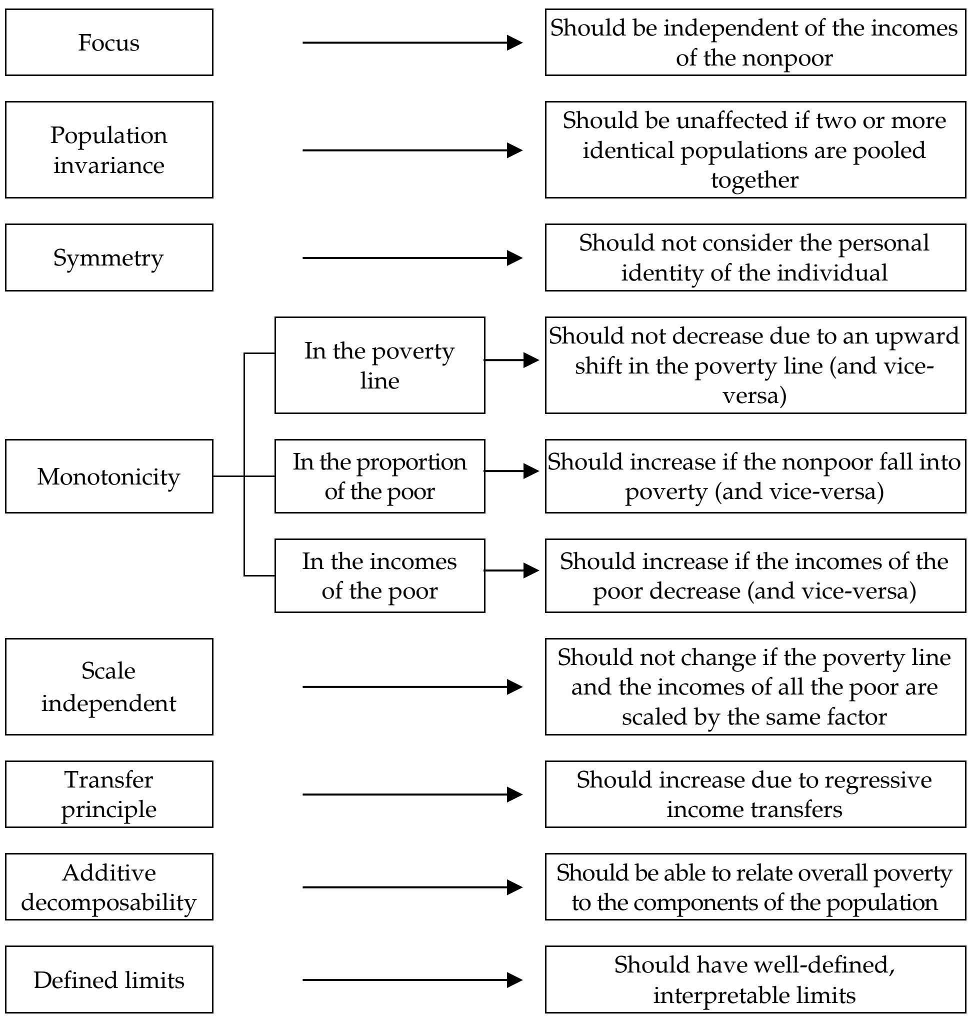
[6] Instead of using food expenditures, many studies, including Ravallion (1994, 1998), Ravallion and Bidani (1994) and Mukherjee and Benson (2003), use total expenditures, which lie around ±5 percent of the food poverty line .

find that the households falling in this range spend very little under heads such as medical care, transport and communication, recreation, education, garments, hoteling and personal appearance.

3.4. *Measuring Poverty*

Having estimated the poverty line, the next step is to gauge the extent of poverty, the most common measure of which is the headcount index introduced by Rowntree (1901). Since then, a large body of literature has developed on various measures of poverty. Selecting the best poverty measure is based on a range of desirable properties, as outlined in Figure 2 (see also the Appendix).

Figure 2: Desirable properties of a good poverty measure



The headcount index, poverty gap index and squared poverty gap index are the most commonly used measures, which fulfill most of the properties listed above, including focus, symmetry, scale independence, decomposability, monotonicity in poverty lines and monotonicity in the proportion of the poor. However, the headcount index and poverty gap index do not satisfy the transfer axiom. The squared poverty gap index is responsive to income redistributions among the poor, but does not have defined, interpretable limits. The present study calculates poverty using these three measures, as each looks at a different dimension of poverty. A brief description of each is given in Table 2.[7]

Table 2: Headcount index, poverty gap and squared poverty gap

Measure	Formula	Definition and features
Headcount index	$P_o = \frac{N_P}{N}$	• Proportion of the population below the poverty threshold level • $0 \leq P_o \leq 1$ • Fails to account for the intensity of poverty • Conditionally satisfies the principle of transfer • Insensitive to income transfers within the poor
Poverty gap index	$P_1 = \frac{1}{N}\sum_{i=0}^{N_P}\left(\frac{g_P}{z}\right) = \frac{1}{Nz}\sum_{i=0}^{N_P}(g_P)$	• Captures the extent to which individuals fall below poverty line and expresses it as a percentage of poverty line • $0 \leq P_o \leq 1$ • Insensitive to income transfers within the poor
Squared poverty gap index	$P_2 = \frac{1}{N}\sum_{i=0}^{N_P}\left(\frac{g_P}{z}\right)^2$	• Weighted sum of poverty gaps as a proportion of poverty line, where the weights are the poverty gaps themselves • Sensitive to income transfers within the poor • $0 \leq P_o \leq \infty$

Note: N_P = the number of poor, N = total population, z = the poverty line, g_P = income gap $(z - Y_P)$ such that $z \geq Y_P$.

[7] P_0, P_1 and P_2 are limiting cases of FGT indices (Foster, Greer & Thorbecke, 1984). These are expressed as $P_\alpha = \frac{1}{N}\sum_{i=0}^{N_P}\left(\frac{g_P}{z}\right)^\alpha$ where α is the poverty aversion parameter and can be interpreted as the weight given to the poor. With α equal to 0, the index becomes P_0, implying that the income shortfalls of the poverty line are given no weight. With α equal to 1, the index becomes P_1, implying that the income shortfalls of the poverty line are given equal weight. Finally, with α equal to 2, the index becomes P_2, implying that the income shortfall of the poverty line is weighted by itself.

The first measure, the headcount index, gives the proportion of households below the poverty line, although it fails to measure the intensity of poverty. The second measure is the poverty gap index, which covers this drawback by considering the extent of poverty and expressing it as a percentage of the poverty line. A problem with the poverty gap index is that it does not consider redistributions of income within the poor, but this shortcoming is resolved by the squared poverty gap.

3.5. Regional Distribution of Poverty

The study has a twofold objective: first, to estimate regional poverty lines and, second, to measure the magnitude and extent of poverty in each region. Having estimated the regional poverty lines and measured poverty in each region, the next task is to determine how regional poverty contributes to overall poverty in Pakistan and thus gauge national estimates of poverty. This is done by aggregating the regional poverty lines and regional poverty levels as follows:

The aggregation of poverty lines is denoted by

$$P_L = \sum_{i=1}^{k} (s_i P_{Li})$$

where P_L is the aggregate poverty line taken as the weighted average of the regional poverty lines (P_{Li}). The weights are the population shares (s_i).

The aggregation of poverty estimates is denoted by

$$P_O = \sum_{i=1}^{k} (s_i P_{oi})$$

where P_O is the overall proportion of poor households, s_i is the population share of poor households belonging to the *i*th region and P_{oi} is the headcount index in the *i*th region.

4. Results and Discussion

This section presents the food and nonfood poverty line estimates for all five regions, followed by a discussion of the extent and intensity of poverty in each region and the results based on the distribution of poverty.

4.1. Estimation of Regional Poverty Lines

The estimates of the food and nonfood poverty lines for the rural and urban segments of each province and Islamabad Capital Territory are presented in Table 3. The food poverty line estimates show that, with the exception of the federal capital territory, the urban poverty line is higher than the rural poverty line in all regions. While food requirements do not vary considerably across rural and urban areas, the difference is in part due to the cost of a basic food bundle. Food items, especially cereals, milk, vegetables, fruit, pulses and meat, tend to be cheaper in rural areas.

Table 3: Estimates of regional food, nonfood and overall poverty lines

		Per adult equivalent poverty lines		
Region		**Food**	**Nonfood**	**Overall**
Punjab	Rural	1,931.76	920.29	2,852.05
	Urban	2,112.57	1,080.34	3,192.91
Sindh	Rural	1,876.65	759.74	2,636.39
	Urban	2,297.85	1,200.92	3,498.77
KP	Rural	2,165.43	1,001.43	3,166.86
	Urban	2,238.22	1,010.03	3,248.25
Balochistan	Rural	1,714.48	851.04	2,565.52
	Urban	1,783.96	913.16	2,697.12
Islamabad Capital Territory	Rural	3,136.72	1,605.59	4,742.31
	Urban	2,752.30	1,390.51	4,142.81

Also, the HIES data for 2013/14 shows that the average price of basic food items, including wheat, wheat flour, rice, rice flour and milk, is about 5 percent lower in rural areas relative to urban areas. Moreover, in rural areas, 37.75 percent of these products come under the category of 'own produced and consumed'. There may also be a difference in consumption bundles, as people in rural areas are less likely to consume readymade and fast foods, which are relatively more expensive.

A different picture surfaces in Islamabad where the food poverty line for rural areas is higher than that for urban areas. A possible reason is that the rural areas of Islamabad do not practice extensive farming and that most of the cereals, meat, vegetables, fruit and milk consumed are supplied from other regions of the country. Moreover, households in rural Islamabad tend to travel to urban areas to purchase food and other essentials. The provincial comparison reveals that the food poverty line is lowest in Sindh, followed by Punjab and Balochistan. This indicates that the cost of living is relatively low in Sindh and Punjab, which could be due to the strong agrarian economy in both provinces.

The estimated nonfood poverty lines follow similar trends, although the magnitude of nonfood poverty expenditures is about half that of food poverty. This is understandable, as the main expenditures of poor and low-income households are food items. The overall poverty lines, which are the sum of the food and nonfood poverty lines, follow a similar pattern.

4.2. *Measurement of Regional Poverty*

To measure regional poverty, we estimate the headcount indices (P0), poverty gap (P1) and squared poverty gap (P2) at the household level, i.e., what proportion of households are poor and what is the depth of poverty. This entails comparing per adult-equivalent household average expenditures with the poverty line, such that households falling short of the poverty line are treated as poor. Next, we consider the number of adult-equivalents in each household and express the poverty estimates in terms of adult-equivalents rather than households (Table 4).

Table 4: Measurement of regional poverty in Pakistan

Region		Poverty measured in terms of households			Poverty measured in terms poor adult equivalents		
		P0	P1	P2	P0	P1	P2
Punjab	Rural	0.216	0.055	0.022	0.274	0.077	0.320
	Urban	0.150	0.030	0.010	0.197	0.043	0.139
Sindh	Rural	0.365	0.113	0.048	0.498	0.168	0.774
	Urban	0.257	0.060	0.025	0.371	0.097	0.432
KP	Rural	0.198	0.031	0.008	0.271	0.045	0.150
	Urban	0.138	0.021	0.005	0.180	0.026	0.058
Balochistan	Rural	0.334	0.095	0.038	0.451	0.139	0.824
	Urban	0.257	0.107	0.050	0.389	0.172	1.315
Islamabad Capital Territory	Rural	0.154	0.036	0.011	0.248	0.067	0.212
	Urban	0.241	0.033	0.027	0.367	0.061	0.458

The estimates of poverty in terms of households show that, with the exception of Islamabad Capital Territory, rural poverty in all the regions is more pronounced. This is interesting because it shows that, despite lower poverty lines, a larger proportion of rural households are poor. In turn, this indicates that general living standards are low in rural areas. This is reflected in the data on average earnings and the proportion of the employed population. According to the HIES (2013/14), average earnings in urban areas are 50 percent greater than those in rural areas. Similarly, the proportion of the employed population (aged 15 or above and currently not enrolled) in urban areas is 10 percent higher relative to rural areas.

The statistics also reveal that the incidence of poverty is far higher in Sindh and Balochistan. This is understandable, given that feudalism and the *vadera* system are much stronger in both provinces.[8] The disaggregated data reveals that more that 40 percent of farmers in Sindh and Balochistan do not own agricultural land and thus work as vassals. Moreover, Sindh experienced heavy floods in 2012, which had an adverse effect on its agricultural output and thus reduced the earnings of small tenants, which in turn led to an increase in poverty in rural Sindh. It is interesting to note that the estimates of the poverty gap (P0) and squared poverty gap (P1) follow a similar pattern, indicating that regions with greater poverty experience extensive poverty, while regions with lower poverty experience less extensive poverty. These findings are consistent with Arif et al. (2016) and Jamal (2017).

The household-level poverty estimates look at the proportion of poor households and their depth of poverty, but ignore household size. Since incorporating household size gives a more accurate picture of poverty, we re-estimate the headcount indices by expressing the number of adult-equivalents belonging to poor households as a proportion of the total number of adult-equivalents. Similarly, we readjust the poverty gap and squared poverty gap for household size.

While the estimates of poverty per adult-equivalent follow a similar pattern to the household-level estimates, the former present a more alarming picture. For instance, 36.5 percent of poor households in rural Sindh comprise 49.8 percent of the total population (measured in terms of adult-equivalents). A similar phenomenon is observed in the other regions. Poverty measured in terms of households reflects that urban KP is the least poor region – 13.8 percent of households are reported to be poor – but this figure jumps to 18 percent when re-estimated in terms of population. Thus, incorporating household size portrays the actual state of poverty overall and indicates that poor households tend to be larger than nonpoor households.

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[8] Under this system, landlords own large tracts of land farmed by small tenants, who often live at subsistence level. Perveen and Dasti (2014), Anwar, Qureshi and Ali (2004) and the Asian Development Bank (2002) argue that feudalism is closely linked to large-scale poverty in Pakistan.

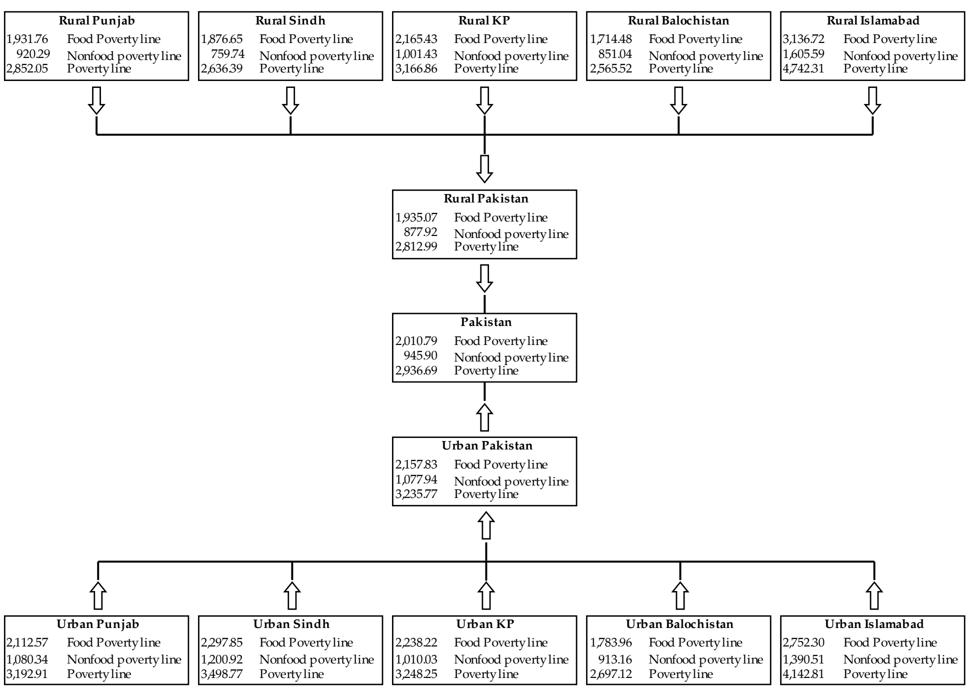
4.3. Regional Distribution of Poverty

Having estimated the region-specific poverty lines and poverty in the rural and urban segments of each province/region, we now assess how poverty in each region contributes to overall poverty in Pakistan and develop estimates of rural, urban and national poverty lines. Aggregating these poverty lines will help gauge the extent of poverty in Pakistan. Finally, we shall also attempt to analyze poverty differentials across rural-urban segments.

4.3.1. Aggregation of Poverty Lines to Obtain National Poverty Lines

The national poverty line is estimated as the weighted average of the regional poverty lines, where the weights are the population shares of each region. The aggregation of the regional poverty lines is presented in Figure 3. The rural poverty line of each region is given at the top of the figure. Each poverty line is then multiplied by the population share of that region. This gives us the rural poverty line for Pakistan. The urban poverty lines are reported at the bottom of the figure and obtained the same way. Finally, the weighted average of the rural and urban poverty lines gives us the national poverty line.

Figure 3: Aggregation of regional poverty lines

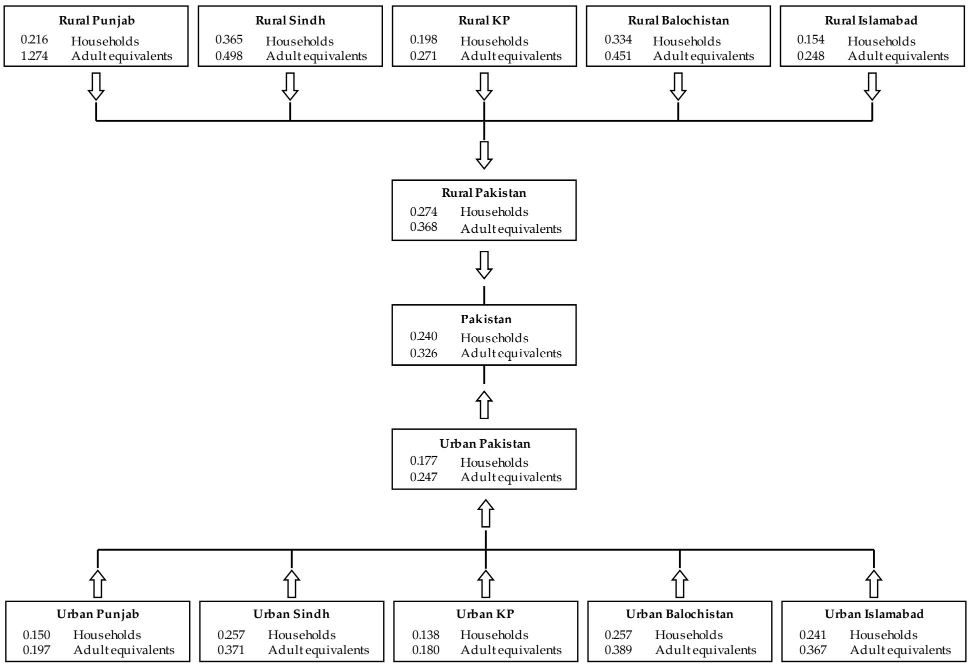


The poverty line for rural Pakistan is PKRs2,812.99 per adult-equivalent (monthly expenditure). For urban areas, it is PKRs3,235.77, which indicates that the cost of maintaining a subsistence level is about 15 percent higher in urban areas. The national poverty line is PKRs2,956.69 per adult-equivalent (monthly expenditure) and is closer to the rural poverty line because 66 percent of the population lives in rural areas. It is worth mentioning that national rural and urban poverty lines do not provide a useful measure of poverty for any specific region of the country. For instance, whereas the national poverty line is PKRs2,956.69, the poverty line for rural KP is PKRs3,166.86. Thus, a household in rural KP with a per adult-equivalent expenditure between these two figures is classified as 'poor' according to the rural poverty line for KP, but 'nonpoor' according to the national poverty line. Aggregation is, therefore, of limited use and can be misleading. To accurately measure poverty, we need to rely on region-specific poverty lines.

4.3.2. Aggregation of Headcount Indices

The aggregation of the regional headcount indices is presented in Figure 4. The headcount index, if defined in terms of adult-equivalents (population), is 0.368 for rural Pakistan, indicating that about 37 percent of the rural population is poor. The urban statistics are better, but not satisfactory, with about 25 percent of the population living below the poverty line. The headcount index for national poverty shows that almost a third of the population falls below the poverty line.

Figure 4: Aggregation of headcount indices measured in terms of households and adult equivalents/population



The Government of Pakistan has increased allocations for social safety net programs such as the Benazir Income Support Program, Pakistan Poverty Alleviation Fund, Waseela-e-Taleem, Apna Rozgar Scheme, Prime Minister's Youth Business Loan and Yellow Cab Scheme. The budgetary allocation to poverty alleviation programs between 2010/11 and 2013/14 was PKRs7,299,397 million – on average equal to 12.9 percent of each year's GDP. However, the continuing high poverty level indicates that the effect of these policies has been limited and far more needs to be done to alleviate poverty.

There may be several reasons for the low impact of these programs. Shirazi and Obaidullah (2014), for instance, point out that the lack of coordination among the agencies managing different safety net programs leads to the duplication of funds at the expense of deserving households. Another reason is the flawed distribution system. For instance, zakat is often distributed on the recommendation of local councilors, politicians and other influential persons, which implies that it does not necessarily reach the most deserving. Arif (2006) notes that, in rural areas, 42 percent of zakat recipients were selected based on the same flawed mechanism. Nayab and Farooq (2014) analyze the effectiveness of the Benazir Income

Support Program and observe that many households receiving continual support are no longer under the poverty line. Hence, imperfect targeting is a key constraint to making these polices more effective.

High inflation is another possible cause of poverty in Pakistan, as it acts as a regressive tax by reducing purchasing power. On average, fixed-salary individuals and low-income households are adversely affected by inflation. During 2010/11 to 2013/14, the average annual inflation rate remained in double digits, which further eroded the purchasing power of low-income households. Different studies, including Braumann (2004), Chaudhry and Chaudhry (2008) and Aftab et al. (2015), argue that inflation adversely affects poverty.

Apart from social and economic factors, individual characteristics such as lack of skills, illiteracy and large households are also associated with poverty. A disaggregated analysis of poor households reveals that about two thirds of household heads are either illiterate or have not even completed primary school. Likewise, 44 percent of poor households have eight or more adult-equivalents, while most poor workers tend to be unskilled (HIES 2013/14).[9]

5. Conclusion

A significant proportion of the population in Pakistan still lives below the poverty line.[10] While most earlier studies have used a single poverty line for the whole country or relied on rural-urban divides, this segmentation fails to incorporate differences across provinces. The present paper attempts to bridge the gap in the literature by estimating region/province-specific poverty lines for the rural and urban segments of each province and the capital territory of Islamabad.

The paper's estimated food poverty lines show that, barring Islamabad, the urban poverty line is higher in all regions – a possible reason being the higher cost of the basic food bundle. A provincial comparison reveals that the food poverty line is lowest in Sindh, followed by Punjab and Balochistan. This indicates that the cost of living is relatively

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[9] In nonpoor households, 46 percent of household heads are illiterate or did not complete primary school, 21 percent of households have eight or more adult-equivalents and a significant proportion of workers are skilled or semi-skilled.

[10] In terms of the population below the poverty line, the World Development Indicators show that, between 2013 and 2015, Pakistan was among the bottom 29 countries out of 81 (for which data was available). If we consider the data for 2007 to 2015, then Pakistan falls among the bottom 42 out of 121 countries.

low in Sindh and Punjab, which may be due to their strong agrarian base. While the estimated nonfood poverty lines follow similar trends, the magnitude of nonfood poverty is about half that of food poverty.

The paper also measures the magnitude and extent of poverty in each region, using headcount indices, poverty gap indices and squared poverty gap indices. We find that poverty estimates in terms of households ignore household size and thus suppress poverty figures. Our estimates show that, with the exception of Islamabad Capital Territory, rural poverty is far more pronounced than urban poverty in all regions. The statistics also reveal that the incidence of poverty is higher in Sindh and Balochistan.

It is interesting to note that the estimates of the poverty gap and squared poverty gap follow a similar pattern, indicating that regions with greater poverty experience extensive poverty while those with lower poverty experience less extensive poverty. In areas such as rural Sindh and Balochistan, more effective policies are needed to counter the effects of feudalism. The government should initiate separate safety nets for poor tenants in these provinces with more emphasis on skills development.

The national poverty line is estimated as the weighted average of the regional poverty lines, equal to PKRs2,956.69 per adult-equivalent (monthly expenditure). The statistics show that about 37 percent of the rural population is poor. The urban statistics are better, but not satisfactory: about 25 percent of the population still lives below the poverty line. The headcount index for Pakistan shows that almost a third of the population falls below the poverty line.

Despite allocating significant funds to social safety net programs, poverty has not declined enough. Part of this is due to the flaws inherent in such programs, such as political influence in the distribution of funds and lack of coordination among the agencies managing different safety net programs. These flaws could be removed though proper planning and management. All schemes could also be better integrated and target the poor more effectively. Finally, a more focused policy to enhance the skills of poor labor is needed, as most households trapped in poverty suffer from a lack of skills.

This study empirically analyzes poverty in the rural and urban segments of each province and the capital territory of Islamabad. Future research at the district level could help uncover the disparities within each province.

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Appendix

Table A1: Per day minimum caloric requirements

Age group	Males	Equivalent factor	Females	Equivalent factor
Less than a year	1,010	0.4297872340	1,010	0.4297872340
01–04	1,304	0.5548936170	1,304	0.5548936170
05–09	1,768	0.7523404255	1,768	0.7523404255
10–14	2,816	1.1982978723	2,464	1.0485106383
15–19	3,087	1.3136170213	2,322	0.9880851064
20–39	2,760	1.1744680851	2,080	0.8851063830
40–49	2,640	1.1234042553	1,976	0.8408510638
50–59	2,460	1.0468085106	1,872	0.7965957447
60 and above	2,146	0.9131914894	1,632	0.6944680851
National average	2,350	1.0000000000		

Source: Government of Pakistan (2003).

Desirable properties of a good poverty measure

- *Focus*: Focuses solely on the incomes of the poor and is not concerned with the incomes of the nonpoor. Any change in the incomes of the poor should affect poverty and any change in the incomes of the nonpoor should not affect poverty.
- *Population invariance*: Should be invariant to the replication of populations. For example, merging two or more identical distributions should not alter the poverty measure.
- *Symmetry*: Should be independent of any characteristics of income units other than the income or welfare indicator being measured.
- *Monotonicity in the poverty line*: Any upward shift in the poverty line should represent an increase in poverty or leave it unchanged and vice versa.
- *Monotonicity in the proportion of the poor*: Poverty increases if the proportion of the poor increases and vice versa.
- *Monotonicity in the incomes of the poor*: Any upward shift in the incomes of the poor should cause a decrease in poverty and vice versa.
- *Scale independent*: Should be invariant to uniform proportional changes: if each income unit's income and poverty line changes by the same proportion, the value of the poverty measure should not change.

- *Transfer principle*: A rank-preserving income transfer from rich to poor or poor to poorer will decrease poverty and vice versa.
- *Decomposability*: Should be able to analyze the contribution of sub-populations to total poverty, such as how poverty in rural and urban segments contributes to overall poverty in a country.
- *Defined limits*: Should have defined, interpretable limits independent of population size. A lower limit of 0 reflects no poverty and an upper limit of 1 indicates 100 percent poverty.

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