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The Statistical Value of Injury Risk in Pakistan's Construction and Manufacturing Sectors

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Abstract

Although health and safety regulations are a key aspect of labor market policymaking, very few studies have examined compensating wage differentials and the statistical value of injury in Pakistan's context. This study looks at injury risk against occupation and industry, using data from the Labor Force Survey for 2013/14. We target five blue-collar occupations in two industries (construction and manufacturing), which tend to account for the highest number of injuries. However, we find that the statistical value of injury in these occupations is too small to reflect the wage premium that workers should be paid for risky jobs.

Keywords: value of injury, industry, labor market conditions, public policy, Pakistan.

JEL classification: O14.

1. Introduction

With a population of approximately 182.1 million (United Nations Population Fund, 2013), Pakistan's total workforce comprises 59.74 million, of which 45.98 million are male and 13.76 million are female (Labor Force Survey for 2012/13). The country ranks 146th out of 187 countries on the 2014 Human Development Index: most of its indicators are below those of other South Asian countries and it has failed to meet several targets under the Millennium Development Goals. In 2013, public spending on education was 2.1 percent of GDP, indicating that education remains a low priority. Similarly, public health expenditure was merely 1 percent of GDP in 2013, making Pakistan one of the world's lowest spenders under this head (World Bank, 2014).

The literature on labor economics uses three different approaches to estimate the statistical value of injury (SVI) or life. The first, developed by Viscusi and Aldy (2003), suggests that workers be compensated for risky

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jobs in the form of wages. The second approach, put forward by Blomquist (2004), entails observing the behavior of workers prepared to undertake risk and measuring its cost. The third is the willingness-to-pay approach, according to which workers are asked how much they are willing to pay to reduce the fatal or nonfatal risk associated with their jobs. This study uses the first approach to estimate a wage-risk premium for workers in Pakistan's manufacturing and construction sectors.

2. Literature Review

Insufficient wage and labor data for developing countries has meant that the literature in this area is scant. The theory of compensating wage differentials itself goes back to Adam Smith, who observed that workers required compensation in the form of higher wages to accept any fatal or nonfatal risk associated with a job. Thaler and Rosen (1976) develop a hedonic wage function that measures the wage-risk tradeoff or wage differential associated with fatal and nonfatal job risk. Schelling (1968) gauges the extent to which workers are willing to accept risk in the process of labor market bargaining over the composition and acceptance or prevention of such risk.

Among more recent studies, Viscusi and Aldy (2003) estimate the value of life by constructing a fatality risk variable based on data for a range of occupations and industries. Using a hedonic wage equation, they find that the value of life is US$4.7 million across the sample, and is US$7.0 million and US$8.5 million for blue-collar male and female workers, respectively. Kluve and Schaffner (2007) examine the impact of compensation for injury risk on the gender pay gap. Finding that male workers are far more likely to be exposed to riskier jobs than female workers, they calculate the observed gender pay gap resulting from job segregation into those that are more dangerous or less so.

Hammitt and Ibarrarán (2006) use compensating wage differentials to estimate the tradeoff between occupational injury risk and income in Mexico City. Their survey provides data on fatal and nonfatal occupational injury risk for a sample of 600 workers, in addition to which they rely on government statistics for actuarial risk data. While the results obtained from the variables that represent workers' subjective perception of risk (based on the survey) may be less reliable, the estimates obtained using the actuarial risk variables are more accurate, given their insensitivity to the omitted variable problem. The values estimated for injury risk are smaller than those for developed countries such as the US, but closer to higher-income countries such as Taiwan and Korea. The results of such studies can be used in cost–benefit analyses to mitigate health and environmental risks in the workplace.

The literature includes a number of studies on compensating wage differentials in labor markets: see, for example, Atkinson and Halvorsen (1990); Shanmugam (2000) and Madheswaran (2004) for India; Liu and Hammitt (1999) for Taiwan; Parada-Contzen, Riquelme-Won and Vasquez-Lavin (2013) for Chile; Polat (2013) for Turkey; and Rafiq and Shah (2010) and Hyder and Behrman (2011) for Pakistan (Table A1 in the Appendix summarizes the literature review). This paper contributes to the literature from a developing country perspective by looking at two different types of risk: the occupational injury risk rate and the industrial injury risk rate. Using both measures provides a broader comparative picture of the SVI in Pakistan's labor market.

3. Data and Summary Statistics

We use data from the Labor Force Survey for 2012/13, drawing on a sample of 6,421 individuals. It is worth noting that the survey has certain limitations: (i) its categorization of occupations and industries restricts the study to 2-digit industries; and (ii) it does not provide any information on the nature of injuries or the number of fatalities, which means that we cannot estimate the cost associated with a particular kind of injury. As a result, the study is restricted to nonfatal risk for which one would expect labor market compensation. Thus, for our purposes, any worker who reported an injury that was followed by a medical consultation is considered a workplace injury.

The hedonic wage equation we estimate takes the log of the hourly wage as a dependent variable. The independent variables include injury risk or nonfatal injury per 100 workers (both industrial and occupational risk), job training, the type of job (permanent or temporary), a regional dummy (urban, rural), provincial dummies, a sector dummy (private, public), human capital variables (age, age-squared and level of education) and two industrial and broad occupational categories. Table 1 presents the study's summary statistics.

The sample includes people of working age, that is, 14–65 years, where age is a proxy for labor market experience is expected to have a positive effect on wages. Age-squared is expected to have a negative sign because it shows how the impact of experience changes over time. While some studies use the Mincer proxy (a school-going age of six years), this does not apply in Pakistan's case where there is no fixed school-going age. Moreover, the high unemployment rate means that not every individual is guaranteed employment after leaving school.

Table 1: Summary statistics

Variable	Percentage
Gender	
Male	93
Female	7
Training	
Trained	26
Not trained	74
Education	
No formal schooling	55
Primary to middle	32
Matriculation	8
Higher	5
Province	
Punjab	19
Sindh	47
KP	26
Balochistan	8
Region	
Rural	56
Urban	44
Industry	
Manufacturing	34
Construction	66
Job status	
Permanent	14
Contractual	61
Without contract	25
Occupation	
Services and market sales	5
Craft and related trades	37
Plant and machine operation	7
Assembly (elementary occupations)	51

Source: Authors' calculations based on data from the Labor Force Survey for 2012/13.

The education variable is divided into five categories: (i) no formal education, (ii) primary schooling but below middle school, (iii) middle schooling but below matriculation, (iv) schooling up to and including matriculation and (v) education beyond matriculation. Technical training is expected to have a positive sign because it is associated with higher wages (75 percent of the workers in our sample had no formal job training). The province variable gauges the wage differential for each of the four provinces. Of the total sample of workers, 19 percent are from Punjab, 48 percent from Sindh, 26 percent from Khyber Pakhtunkhwa (KP) and 8 percent from Balochistan. In addition, the model includes job-related characteristics such as employment sector and the type of job held.

To enable a more detailed analysis, we include the occupational and industrial injury rates and associated demographics. As Table 2 shows, the occupational injury variable has a very high standard deviation because the severity of risk varies widely by occupation: those such as firefighting, kiln work and mining, for example, carry a higher risk than others. However, there may be less variation in the injury rate because a given industry will comprise numerous occupations, thus lowering the deviation of risk.

Table 2: Occupational injury rate, by industry

Variable	Mean	Standard deviation
Injury rate in industry	6.00	2.34
Injury rate in occupation	5.93	5.90

Note: Per 100 workers.
Source: Authors' calculations based on data from the Labor Force Survey for 2012/13.

Table 3 shows that men are exposed to greater risk of injury in the labor market than women, who tend to be more risk-averse and less likely to opt for high-risk, physically demanding occupations.

Table 3: Average industrial injury rate, by gender

Gender	Injury rate by industry	Injury rate by occupation
Male	6.21	6.08
Female	2.64	3.80

Note: Per 100 workers.
Source: Authors' calculations based on data from the Labor Force Survey for 2012/13.

4. Construction of Injury Rate Variables

The hedonic wage equation includes an industrial injury risk variable that is calculated using the formula adopted by the US Bureau of Labor Statistics:

$$\textit{Industrial injury rate} = N/H \times 200{,}000$$

where N is the total number of injuries to have occurred in a given industry[1] and H is the total number of hours worked by all employees in that industry in a year. The figure 200,000 is a combined base scaling the total number of hours worked by 100 workers in a year – a technique also used by Hersch (1998). Table A2 in the Appendix lists the 2-digit industries covered by the study.

The same method is used to calculate the occupational injury rate:

$$\textit{Occupational injury rate} = N/H \times 200{,}000$$

where N is the total number of injuries to have occurred in a given occupation and H is the total number of hours worked by all employees in that occupation in a year. Again, 200,000 is a combined base scaling the total number of hours worked by 100 workers in a year. Table A3 in the Appendix lists the blue-collar occupations covered by the study.

5. Theoretical Model

Under the hedonic wage model, the demand for labor is a decreasing function of the cost of employing labor, i.e., as the cost of employing a worker rises, the demand for his or her labor falls. This cost includes salary and compensation as well as the cost of providing medical care, training and a safe working environment. For a given level of profit, firms will pay their workers less as these costs increase. Thus, workers will choose a wage-risk combination that yields the highest wage.

The hedonic wage function we employ is adapted from the models developed by Viscusi (2003) and Elia, Carrieri and Di Porto (2009). We assume that risk has a price in the form of a wage premium, such that workers are willing to reduce the probability of injury or death by forgoing part of this wage premium. Thus, firms and workers set a wage-risk combination (w, r) in the implicit labor market.

[1] The survey asks respondents if, in the last 12 months, they have suffered any occupational injury or disease that led them to take time off work and/or consult a doctor.

We also assume that a worker's decision to work in a certain occupation or industry depends solely on the associated risk and wage rate. Let $U(w)$ denote the utility function of a healthy worker and $V(w)$ the utility function of a nonhealthy or injured worker at wage w. Assuming that a worker would rather be healthy than injured, $U(w) > V(w)$. In both cases, the marginal utility of the wage rate is positive: $U'(w) > 0$, $V'(w) > 0$.

If f is the likelihood of an accident (nonfatal), then the expected utility function of a worker will be:

$$Q = (1 - f)U(w) + fV(w) \tag{1}$$

Differentiating equation (1) with respect to f and w, we obtain the wage-risk tradeoff:

$$\frac{dw}{df} = -\frac{Q_f}{Q_w} = \frac{\mathrm{U(w)} - V(w)}{(1-f)U'(w) + fV'(w)} > 0 \tag{2}$$

Equation (2) shows that, as the level of risk increases, so does the wage rate – this is the compensating wage differential. The wage-risk tradeoff is, therefore, obtained by differentiating both utilities with respect to the marginal utility of wages.

6. Empirical Model

To calculate the SVI, we estimate the hedonic wage equation by regressing the log of the hourly wage on the model's independent variables – province, region, age, education, experience, industrial and occupational dummies and injury risk – using a semi-log linear model:

lnwage = f (human capital variables and individual characteristics, residential characteristics, job characteristics, injury rate) (3)

Equation (3) is estimated twice,[2] first using the occupational injury rate and then the industrial injury rate. The log of hourly wages is constructed by dividing the weekly wage of the *i*th worker by the total number of hours he/she has worked that week.[3] The SVI is then calculated as follows:

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[2] While computing this specification without the log of hourly wages yields similar results, the F-test statistics clearly support the use of *lnwage*. It also normalizes the distribution.

[3] In using this model, one concern is that workers do not select jobs at random and their preferences are unobserved. The literature on the statistical value of life or injury does not address this problem of self-selection per se. The most common method used is the Heckman two-stage procedure, which involves a discrete choice variable. Some studies employ union membership as the discrete choice variable at the

$$SVI = \beta * \overline{\omega} * 2{,}000 * 100 \tag{4}$$

where β is the coefficient of the injury risk variable and $\overline{\omega}$ is the mean wage of all workers multiplied by 2,000 (as the total number of hours worked in a year to annualize the value) and then multiplied by 100 as the scale of the variable (per 100 workers).[4]

7. Results and Discussion

Table 4 gives the estimates obtained from the two hedonic wage equations specified earlier. In the first model, the injury risk variable is based on the 2-digit industry injury rate. The second model includes the 2-digit occupation injury rate besides other control variables. Both sets of results exhibit a parabolic age-earning profile. Male workers receive higher wages than their female counterparts. The training variable is significant and negative and shows that workers without job training are paid 12 percent less than trained workers.[5] The education category estimates are in line with human capital theory.

Table 4: Regression results for two hedonic wage equations

	Dependent variable = log of hourly wages		
Independent variables	**Model 1**	**Model 2**	**Model 3**
Industrial injury rate	0.006	–	
	(0.005)		
Occupational injury rate	–	0.023***	-0.043
		(0.006)	(0.038)
Occupational injury rate squared			0.006**
			(0.0028)
Controls			
Age	0.190***	0.190***	0.0180***
	(0.004)	(0.004)	(0.0039)
Age squared	-0.0002**	-0.0002**	-0.0002***
	(0.00005)	(0.00005)	(0.00005)
Gender (ref. = male)			
Female	-0.326***	-0.310***	-0.303***
	(0.039)	(0.038)	(0.037)
Training (ref. = trained)			

first stage – see, for example, Marin and Psacharopoulos (1982) – but we are restricted to very limited choice variables as the Labor Force Survey does not provide any data on union membership.

[4] 2,000 is the annual average number of hours worked, used globally (see Viscusi, 2003).

[5] All the dummy coefficients are calculated by the following formula $100(e^{coefficient} - 1)$ (see Halvorsen & Palmquist, 1980).

Independent variables	Model 1	Model 2	Model 3
Untrained	-0.115***	-0.120***	-0.131***
	(0.022)	(0.022)	(0.021)
Education (ref. = no schooling)			
Primary to middle	0.062***	0.064***	-0.016
	(0.016)	(0.016)	(0.017)
Matriculation	0.053**	0.052**	0.216***
	(0.026)	(0.027)	(0.027)
Above matriculation	0.059*	0.058*	0.054**
	(0.032)	(0.032)	(0.021)
Province (ref. = Punjab)			
Sindh	-0.153***	-0.155***	-0.150***
	(0.017)	(0.017)	(0.016)
KP	-0.362***	-0.362***	-0.356***
	(0.023)	(0.024)	(0.023)
Balochistan	0.274***	0.276***	0.270***
	(0.037)	(0.037)	(0.034)
Region (ref. = rural)			
Urban	0.091***	0.080***	0.080***
	(0.015)	(0.015)	(0.014)
Job status (ref. = permanent)			
Contractual	0.194**	0.196***	0.215**
	(0.086)	(0.084)	(0.083)
Without contract	0.070	0.081	0.081
	(0.064)	(0.064)	(0.064)
Industry (ref. = manufacturing)			
Construction	0.377**	0.318***	0.312***
	(0.025)	(0.029)	(0.030)
Occupation (ref. = services and sales)			
Craft and related trades	-0.197	-0.318*	-0.116
	(0.132)	(0.133)	(0.149)
Plant and machine operation and assembly	-0.175	-0.291*	-0.080
	(0.141)	(0.141)	(0.161)
Elementary occupations	-0.514***	-0.591***	-0.326**
	(0.133)	(0.131)	(0.168)
Constant	3.601***	3.631***	3.570
	(0.168)	(0.164)	(0.160)
F-statistic	127.60	135.80	128.88
Adjusted R^2	0.220	0.222	0.222

Note: Robust standard errors given in parentheses. * = significant at 10% level, ** = significant at 5% level, *** = significant at 1% level

Source: Authors' calculations based on data from the Labor Force Survey for 2012/13.

The province dummies are included in the regression to capture the wage differential between each province relative to Punjab. Both the province and urban/rural dummies are significant, showing that workers' place of residence has a significant effect on their wages. With respect to the job characteristic variables, the estimates show that contractual jobs pay a significantly higher wage than permanent jobs. The 1-digit industry dummy is used to measure the effect of working in a particular industry and its coefficient shows that workers in construction earn 30–40 percent more than their counterparts in manufacturing.

The injury risk variable is the focus of this study. Its estimated coefficient in model 1 is positive but not statistically different from 0, while the occupational injury risk variable in model 2 is positive and statistically significant at the 1 percent level. The estimated beta of occupational injury risk in model 2 demonstrates that workers are compensated very poorly for the risk they assume at the workplace. The coefficient of occupational injury risk is 0.023, indicating that a 1 percent increase in injury risk raises the wage level by 2.3 percent.

The difference between the occupational and industrial injury rates is interesting. While an industry comprises a range of occupations (for instance, manufacturing includes assembly and operation, craft and related trades, services and marketing), which lowers the average risk rate, an occupation consists of a specific task associated with a specific injury rate. This is an important finding because it implies that the occupational injury rate is a better measure of exposure to risk.

The SVI per 100 workers is calculated as follows:

$$SVI = \beta * \bar{\omega} * 2{,}000 * 100 \qquad (4)$$

SVI_1 is based on the industrial injury rate and has an insignificant coefficient.

SVI_1 = 0.006*43*2,000*100

= PKR 51,600/100 workers/year

= PKR 43/ worker/month[6]

[6] At the lower and upper confidence interval levels, the value of SVI_1 for the industrial injury rate is 42.34 and 44.94, respectively.

SVI_2 is based on the occupational injury rate and has a significant coefficient.

SVI_2 = 0.023*43*2,000*100

= PKR 197,800/100 workers/year

= PKR 165/worker/month[7]

Given that the result for occupational injury risk is significant, we also estimate the impact of the occupational injury rate squared to assess the nonlinear relationship between injury risk and the wage rate. Applying the results of model 3 to an occupational injury rate ranging from 0 to 11.5, the labor market begins to pay a premium after the occupational injury rate crosses 3.5, on average. Our final calculation, SVI_3, represents the nonlinear relationship between the occupational injury rate and the wage premium.

In the linear model 2, the wage depended on β*(injury rate) so that dw/d(injury rate) = β in the SVI_2 formula. However, in the nonlinear model 3, the wage depends on β_1*(injury rate) + β_2*(injury rate squared), such that dw/d(injury rate) = $\beta_1 + 2\beta_2$*(injury rate) is the new β. Since this β is no longer constant, we evaluate it at the average occupational injury rate and then apply the SVI formula to determine SVI_3:

SVI_3 = [– (0.043) + 2(0.006)*(average injury rate)]*43*2,000*100

= [– (0.043) + 2(0.006)*(5.93)] *43*2,000*100

= 0.0281*43*2,000*100

= PKR 242,176/100 workers/year

= PKR 201/ worker/month[8]

These figures show that blue-collar workers in Pakistan are paid a relatively small compensating wage differential. High unemployment and the abundance of labor, which gives workers a weaker bargaining position, is a likely contributor to this small differential. Our results are consistent with Elia et al. (2009), where unemployment, job scarcity and

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[7] At the lower and upper confidence interval levels, the value of SVI_2 for the occupational injury rate is 161.30 and 172.27, respectively.

[8] At the lower and upper confidence interval levels, the value of SVI_3 for the occupational injury rate is 195.0 and 206.9, respectively.

labor abundance explain the absence of an adequate wage premium for risky jobs.

Our results highlight the inadequacies of labor market institutions and the weak bargaining position of workers in Pakistan, which, when combined with the large supply of labor, open up further opportunities for labor exploitation. Another important implication of these estimates is that the occupational injury rate is a more meaningful indicator of risk than the industrial injury rate.

8. Conclusion

This study draws on a sample of blue-collar workers in construction and manufacturing to estimate the SVI for Pakistan's labor market. The industries and occupations selected account for the highest number of injuries in a one-year period relative to other occupations and industries, implying that workers in these sectors are exposed to greater risk of injury. Workers in construction earn more than their counterparts in manufacturing.

The estimates we obtain do not validate the theory of compensating wage differentials to a satisfactory degree: these differentials are negligible and insufficient to cover the cost of damaged health among workers. One possible explanation is that, given Pakistan's high unemployment rate (above 6 percent), people are more willing to accept riskier jobs even if they are not compensated fully for the risk they assume. These results indicate that the area needs further research.

References

Atkinson, S. E., & Halvorsen, R. (1990). The valuation of risks to life: Evidence from the market for automobiles. *Review of Economics and Statistics*, *72*(1), 133–136.

Blomquist, G. C. (2004). Self-protection and averting behavior, values of statistical lives and benefit cost analysis of environmental policy. *Review of Economics of the Household*, *2*(1), 89–110.

Elia, L., Carrieri, V., & Di Porto, E. (2009). *Do you think your risk is fair paid? Evidence from Italian labor market* (Working Paper No. 89). Turin: LABOR (Center for Employment Studies).

Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review*, *70*(3), 474–475.

Hammitt, J. K., & Ibarrarán, M. E. (2006). The economic value of fatal and non-fatal occupational risks in Mexico City using actuarial- and perceived-risk estimates. *Health Economics*, *15*(12), 1329–1335.

Hersch, J. (1998). Compensating differentials for gender-specific job injury risk. *American Economic Review*, *88*(3), 598–607.

Hyder, A., & Behrman, J. R. (2011). Schooling is associated not only with long-run wages, but also with wage risks and disability risks: The Pakistani experience. *Pakistan Development Review*, *50*(4), 555–573.

Kluve, J., & Schaffner, S. (2007). *Gender wage differentials and the occupational injury risk: Evidence from Germany and the US* (Ruhr Economic Paper No. 28). Duisburg: University of Duisburg-Essen.

Krueger, A. B., & Summers, L. H. (1988). Efficiency wages and the inter-industry wage structure. *Econometrica*, *56*(2), 259–293.

Liu, J.-T., & Hammitt, J. K. (1999). Perceived risk and value of workplace safety in a developing country. *Journal of Risk Research*, *2*(3), 263–275.

Madheswaran, S. (2004). *Measuring the value of life and limb: Estimating compensating wage differentials among workers in Chennai and Mumbai* (Working Paper No. 9-04). Kathmandu: South Asian Network for Development and Environmental Economics.

Marin, A., & Psacharopoulos, G. (1982). The reward for risk in the labor market: Evidence from the United Kingdom and a reconciliation with other studies. *Journal of Political Economy*, *90*(4), 827–853.

Nakata, A., Ikeda, T., Takahashi, M., Haratani, T., … Araki, S. (2006). Impact of psychosocial job stress on non-fatal occupational injuries in small and medium-sized manufacturing enterprises. *American Journal of Industrial Medicine*, *49*(8), 658–669.

Parada-Contzen, M., Riquelme-Won, A., & Vasquez-Lavin, F. (2013). The value of a statistical life in Chile. *Empirical Economics*, *45*(3), 1073–1087.

Polat, S. (2013). *Wage compensation for risk: The case of Turkey* (GIAM Working Paper No. 13-11). Istanbul: Galatasaray University, Economic Research Center.

Rafiq, M., & Shah, M. K. (2010). The value of reduced risk of injury and deaths in Pakistan – using actual and perceived risk estimates. *Pakistan Development Review*, *49*(4), 823–827.

Schelling, T. C. (1968). The life you save may be your own. In S. B. Chase (Ed.), *Problems in public expenditure analysis* (pp. 127–162). Washington, DC: Brookings Institution.

Shanmugam, K. R. (2000). Valuations of life and injury risks. *Environmental and Resource Economics*, *16*(4), 379–389.

Thaler, R., & Rosen, S. (1976). The value of saving a life: Evidence from the labor market. In N. E. Terleckyj (Ed.), *Household production and consumption*. New York: National Bureau of Economic Research.

United Nations Population Fund. (2013). *The state of world population 2013: Motherhood in childhood*. New York: Author.

Viscusi, W. K. (2003). *The value of life: Estimates with risks by occupation and industry* (Discussion Paper No. 422). Cambridge, MA: Harvard Law School, John M. Olin Center for Law, Economics and Business.

Viscusi, W. K., & Aldy, J. E. (2003). *The value of a statistical life: A critical review of market estimates throughout the world* (Working Paper No. 9487). Cambridge, MA: National Bureau of Economic Research.

World Bank. (2014). *Pakistan: Country partnership strategy for the period FY2015–19*. Washington, DC: Author.

Appendix

Table A1: Summary of literature review

Study	Country	Data source	Methodology	Outcome
Krueger and Summers (1988)	US	US Census Bureau 1974 and 1979, population survey for 1984	Standard deviations	The industry wage structure is remarkably stable across regions and time, but a detailed micro-analysis shows slight wage differentials based on the characteristics of the work performed.
Viscusi (2003)	US	Bureau of Labor Statistics 1992–97	Hedonic wage equation, OLS	Blue-collar women have higher compensating wage differentials than blue-collar men.
Viscusi and Aldy (2003)	US	Bureau of Labor Statistics	Hedonic wage equation, OLS	Nonunion members have lower risk premiums. VSL decreases with age.
Kluve and Schaffner (2007)	Germany and the US	German Socioeconomic Panel, Panel Study of Income Dynamics	Hedonic wage equation, OLS	Men are exposed to riskier, more dangerous work than women.
Polat (2013)	Turkey	Ministry of Labor and Social Security, Household Labor Force Survey 2010–11	Hedonic wage model, OLS	The injury risk premium is pertinent in all sectors. In the case of fatal risk, it is limited to manufacturing.
Nakata et al. (2006)	Japan	Survey	Multivariable logistic regression	There is an expected increase in the risk of occupational injury among current and former male smokers and a risk factor for nonsmokers through passive smoking.
Hersch (1998)	US	Bureau of Labor Statistics	Hedonic wage equation, OLS	Adjusting for the number of women in employment, they are 71 percent as likely as men to get injured.

Study	Country	Data source	Methodology	Outcome
Elia, Carrieri and Di Porto (2009)	Italy	Survey of Household Income and Wealth	Hedonic wage equation, OLS	Small firms pay their workers a flat wage risk premium. The wage-risk tradeoff does not always emerge as hedonic wage theory would predict.
Marin and Psacharopoulos (1982)	UK	Office of Population Censuses and Surveys	Hedonic wage model, OLS, semi-log linear model	Workers are compensated for risk even if they are not union members.
Shanmugam (2000)	India	Survey 1990	Hedonic wage equation, OLS	Minor compensating wage differentials exist.
Madheswaran (2004)	India	Survey and interviews	Hedonic wage equation, OLS	The labor market pays INR240 as an annual wage premium for risky jobs.
Hammitt and Ibarrarán (2006)	Mexico	Survey	Hedonic wage regression, OLS	The SVI is smaller than in the US, but almost the same when compared to Taiwan and South Korea.
Liu and Hammitt (1999)	Taiwan	Survey and interviews, Chilean Safety Association	Hedonic wage function, OLS	Petrochemical workers receive a significant compensating wage differential for risky jobs.
Parada-Contzen, Riquelme-Won and Vasquez-Lavin (2013)	Chile	Chilean Safety Association	Hedonic wage model, OLS, probit model	A wage premium exists. The results are consistent with other developing countries.
Rafiq and Shah (2010)	Pakistan	Punjab Employees Social Security Institute (only for Lahore	Hedonic wage model, OLS	Workers are compensated for risk in selected private sector firms in Lahore.

Table A2: Classification of 2-digit level industries

Code	Industry
	Manufacturing
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related
16	Manufacture of wood and its products and cork manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastics
23	Manufacture of other nonmetallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery
	Construction
41	Construction of buildings
42	Civil engineering
43	Specialized construction activities

Source: Pakistan Standard Industrial Classification (all economic activities) Rev. 4 (2010).

Table A3: Classification of blue-collar occupations

Occupation	Sub-occupation
Services shop and market sales	Personal and protective services
	Models, sales and demonstrations
	Extraction and building trades
Craft and related trades	Metal, machinery and related trades
	Precision, handicraft, printing and related trades
	Other craft and related trades
Plant and machinery operation and assembly	Stationary plant and related operation
	Machinery operation and assembly
	Driving and mobile plant operation
Elementary occupations	Sales and services elementary occupations
	Labor in mining

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Agglomeration and Firm Turnover in Punjab

Marjan Nasir*

Abstract

The literature on industrial organization shows that geographic and industrial concentration affects firm turnover. This study conducts a firm-level analysis to gauge the impact of agglomeration on firm entry and exit in domestic industries in Punjab, Pakistan. It also illustrates how certain industries exist in clusters while others are highly dispersed. The results suggest that higher rates of firm entry and exit are associated with highly agglomerated industries.

Keywords: agglomeration, firm entry, firm exit, Pakistan.

JEL classification: D22, L16.

1. Introduction

While the literature on industrial organization has traditionally highlighted the role of new firms as stimulators of economic development, more recent research has focused on the factors affecting the establishment and performance of new firms. Firm entry is associated with employment changes, product and technological innovation and other structural changes in the industry concerned. Furthermore, as incumbent firms face greater competition from new firms, this results in improved productivity, which might otherwise have crowded them out. This paper looks at the effect of agglomeration on firm entry and exit in Punjab's manufacturing sector.

Evidence of industrial agglomeration and the factors causing the geographical concentration of firms in Pakistan has been put forward by Burki and Khan (2010). They show that industries tend to be concentrated in districts with an infrastructure (in the form of road density), access to markets and resources such as skilled labor. Accordingly, new firms are more likely to locate near similar firms to take advantage of positive spillovers in the form of shared resources and knowledge or technological spillovers.

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The study's aim is to determine why industrial agglomeration tends to attract new businesses. The literature on industrial organization in Pakistan has not studied firm entry and exit rates or their determinants primarily due to insufficient data. This study uses data from the Punjab Directory of Industries, available for 2002, 2006 and 2010, to map selected industries in which firms either exist in clusters or are highly dispersed. It thus aims to contribute to the existing literature by looking at the impact of spatial and industrial concentration on the entry and exit rates of manufacturing firms in Punjab. The results support other studies that have found that firm entry and exit rates are higher in more agglomerated industries.

The literature on firm entry and agglomeration is discussed in Section 2. Section 3 presents a theoretical model, Section 4 describes the data used, which is then mapped in Section 5. The econometric model and results are presented in Sections 6 and 7, respectively. Section 8 concludes the paper.

2. Literature Review

Studies in this field have looked at factors that limit or attract the entry of new establishments by analyzing the manufacturing, retail and nonfinancial sectors at the firm or plant level. According to Hopenhayn (1992), firms in the manufacturing sector tend to be replaced by new entrants over five-year periods, with a similar trend in job turnover. The literature on firm entry differentiates between new entrants – also referred to as 'greenfield' firms – and existing or diversifying firms that have set up plants in different geographical areas and/or expanded their range of products.

The importance of studying entry rates lies in their contribution to regional development. Whether these benefits are direct (such as job creation) or indirect (such as improvements in supply conditions), new establishments tend to stimulate economic development. They augment the industry's resource flows (Roberts & Thompson, 2003) by affecting its productivity and contributing to product and technological innovation. Moreover, these entrants increase competition in the existing market, thus affecting firms' output, pricing and nonpricing decisions. However, Fritsch and Mueller (2004) suggest that these benefits can take as long as eight years to materialize.

Several studies have looked at agglomeration as a source of firm entry and exit, including Devereux, Griffith and Simpson (2004); Dumais, Ellison and Glaeser (2002); Carlton (1983); Rosenthal and Strange (2010); and De Silva and McComb (2011). Their findings suggest that agglomeration has a significant impact on the entry of small firms and low-tech firms and on the survival rate of existing firms. New firms or plants are likely to locate near their input suppliers or similar establishments because this allows them to take advantage of positive externalities in the form of labor pooling or technology and knowledge spillovers. These effects vary across industries as well as geographical areas.

In the case of manufacturing plants, Dumais et al. (2002) suggest that firm exit contributes to a decline in industrial concentration while new plant entry leads to firm clustering. This suggests that a region's acquired characteristics, rather than its endowed resources, are an important factor in firm location. Porter (2000) explains that new businesses are more likely to be established within a cluster rather than in a remote area, given lower barriers to entry and exit and because resources such as assets, skills and inputs are more readily available. While this leads to higher entry rates in a cluster, it also means that exit rates remain high because firms require less specialized investment.

The combination of lower entry/exit barriers and greater competition from incumbent firms in that cluster results in higher entry and exit rates for firms in agglomerated industries. Firm survival becomes more difficult, the more agglomerated the industry: the competition from incumbent firms rises as resources become more accessible, together with increasing spillover benefits. However, there is also evidence that agglomeration can have a negative effect on new firm entry – measured by their share of employment – especially for large firms, which seem to be more integrated than small firms. This would suggest that new firms are more likely to locate where there is less geographical concentration of similar firms, although the risk of closure is also more pronounced among these firms.

The Ellison–Glaeser index (EGI) of agglomeration uses the Gini coefficient to measure raw geographical concentration and the Herfindahl index of industrial concentration to determine whether an industry is agglomerated (Ellison & Glaeser, 1997). The index requires employment data to calculate these ratios: a highly agglomerated industry will have a high, positive value while a low or negative value implies that the industry is dispersed. An intermediate index value points to a moderately agglomerated industry. This paper uses the EGI to measure agglomeration.

3. Agglomeration and Firm Entry in Domestic Industries

The theoretical background and model in this section relates agglomeration, through knowledge spillovers, to firm entry, assuming all other domestic and foreign factors affecting firm entry are held constant. Marshall (1920) argues that geographical concentration or the clustering of industries enhances learning and the exchange of knowledge among firms. This implies that similar firms will locate near each other to take advantage of these spillovers.

Soubeyran and Thisse (1998), who introduce a formalized model of this notion, look at knowledge spillovers (technological externalities) in districts with agglomerated industrial clusters that have attracted new firms. Knowledge spillovers are acquired through learning-by-doing: workers within a particular geographical boundary are likely to share information and ideas with each other, which eventually increases their productivity as firm employees. The model assumes that labor is immobile between geographic locations such as districts and, therefore, that knowledge spillovers are limited to that geographical area or industrial cluster. Moreover, the higher the stock of knowledge or spillover effects in a cluster, the more attractive the industrial cluster becomes to new firms.

The model developed by Soubeyran and Thisse (1998) comprises a set of locales denoted by M, with $x \in M = \{1, \ldots, m\}$. Each locale x in period t has a fixed labor supply L_t^x, an initial stock of knowledge $S_0^x \geq 0$ and an identical continuum of entrepreneurs who can start a new firm with capital K_t^x at interest rate r_t and sell homogenous goods in the world at price p_t. There is an infinite number of periods $t = 1, 2\ldots$ and entrepreneurs can set up a firm in a new locale in any new period. In order to incorporate Marshallian industrial districts (indicating an agglomerated industrial area), the model assumes that labor will accumulate knowledge over time through different social interactions (the spillover effect). Firms can take advantage of these spillovers only if they locate in x. Finally, it assumes that $\ell'(S_{t-1}^x) < 0$.

The cost function faced by a firm in locale x in period t is given by:

$$C_t^x(q_t^x, w_t^x, S_{t-1}^x) = w_t^x \ell(S_{t-1}^x) q_t^x + r_t K(q_t^x) \tag{1}$$

where q_t^x is output, w_t^x denotes wages and S_{t-1}^x is the sum of past production. The labor coefficient $\ell(S_{t-1}^x)$ takes into account the skills accumulated by workers through knowledge spillovers over time: the more knowledge spillovers, the higher the skills accumulated over time. The amount of capital $K(q_t^x)$ required by a new firm is constant across locales.

The profit of a firm established in locale x in period t is denoted by:

$$\Pi_t^x(q_t^x, w_t^x, S_{t-1}^x) = p_t q_t^x - C_t^x(q_t^x, w_t^x, S_{t-1}^x) \tag{2}$$

Firms deciding to enter a new locale in period t will maximize their profit Π_t^x with a negligible impact on total industry output. The term S_{t-1}^x is the technological externality (knowledge stock) affecting the firms in that locale or industry. Differentiating equation (2) with respect to S_{t-1}^x yields the effect of knowledge on the firm's profit:

$$\frac{\partial \hat{\Pi}_t^x}{\partial S_{t-1}^x} = -w_t^x \hat{q}_t^x \ell'(S_{t-1}^x) > 0 \qquad (3)$$

Equation (3) shows that firm profits in a locale increase with the knowledge stock accumulated therein. The following expression indicates positive production by firms:

$$\hat{q}_t^x = (K')^{-1}\{[p_t - w_t^x \ell(S_{t-1}^x)]/r_t]\} \qquad (4)$$

Given w_t^x and S_{t-1}^x, equation (3) is maximized with respect to q_t^x to obtain:

$$\frac{\partial \pi_t^x}{\partial q_t^x} = P_t - w_t^x \ell(S_{-1}^x) - r_t K'(q_t^x) \leq 0,\, q_t^x \frac{\partial \pi_t^x}{\partial q_t^x} = 0,\, q_t^x \geq 0 \qquad (5)$$

This partially satisfies the second-order condition. Let $\hat{q}_t^x$ be the unique solution to equation (5). The following expression indicates positive production by firms:

Combining equations (5) and (2) gives the value function:

$$\hat{\Pi}_t^x = \Pi_t^x[\hat{q}_t^x(w_t^x, S_{t-1}^x, r_t, p_t), w_t^x, S_{t-1}^x] = \hat{\Pi}_t^x(w_t^x, S_{t-1}^x, r_t, p_t) \qquad (6)$$

This can be summarized as:

$$\hat{\Pi}_t^x = r_t \lambda(\hat{q}_t^x) \qquad (7)$$

Equation (7) denotes the maximum profit a firm can make when set up in locale x. This helps determine the equilibrium distribution of firms across locales.

In the model's short-run equilibrium, no firms are set up in $t = 0$ and the initial stock of knowledge is $S_0^x \geq 0$. To maximize profits, firms are set up in locale x in $t = 1$ and are attracted to those locales where the stock of knowledge is highest, indicating a more productive labor force. In equilibrium, profits are equal across locales. Given full employment, the number of firms (n_t^x) in locale x is:

$$n_t^x = L^x / \hat{q}_t^x \ell(S_{t-1}^x) \tag{8}$$

The condition that profits are equal across locales, together with equation (8), implies that $r_t \lambda(\hat{q}_t^x) = r_t \lambda(\hat{q}_t^y)$ with $x, y \in I_t$ (where I_t represents the locales in which firms have been established). This shows that firm output in equilibrium is the same across locales. The equilibrium output is denoted by:

$$\hat{q}_t(I_t) = \sum_{x \in M} L^x v(S_{t-1}^x), \quad \text{where } v \text{ is strictly increasing} \tag{9}$$

Combining equations (9) and (8) yields the equilibrium distribution of firms:

$$n_t^x(I_t) = \frac{L^x v(S_{t-1}^x)}{\sum_{y \in I_t} L^y v(S_{t-1}^y)}, \quad x \in I_t \tag{10}$$

The interpretation of equation (10) is important: it shows that the higher the stock of labor (L) or knowledge spillovers (S) in locale I_t, the higher the number of new firms (n) that will locate there.

4. Data and Descriptive Statistics

This study uses data from the Directory of Industries compiled by the Punjab government for 2002, 2006 and 2010. It includes approximately 18,000 manufacturing firms – giving the name and address of each – in nearly 180 industries (2-digit) in Punjab. Other information includes the year of establishment, employment and initial investment. The employment data was used to calculate the agglomeration index and determine firm size while initial investment was used as a control factor as a proxy for sunk costs. The industry and firm descriptive statistics are presented in Table 1.

Table 1: Descriptive statistics for all industries, 2006

Number of industries	180
Number of firms	18,007
Mean firm age (years)	17
Mean number of employees	48
Mean industry entry rate	0.10
Mean industry exit rate	0.25
Mean industry EGI (2002)	0.1554
Mean industry output growth (percent)	86
Mean initial investment (PKR '000)	40,892

Source: Government of the Punjab, Directory of Industries for 2006.

There were 180 (2-digit) industries comprising 18,007 firms in Punjab in 2006. On average, each firm had been in operation for 17 years and employed around 48 workers. From 2002 to 2006, the mean firm entry rate was 10 percent and the exit rate was 25 percent. On average, the industries had become more agglomerated, as indicated by a positive EGI. Output growth remained high across all industries over this period, with firms undertaking an initial investment of approximately PKR 40 million, on average (with a median value of PKR 2,648,000).

Table 2 lists the top 20 industries in Punjab in descending order of entry, while Table 3 lists the top 20 industries in descending order of exit. Table 4 gives the EGI for the 20 most agglomerated industries.

Table 2: Top 20 industries with the highest entry rates in Punjab, 2006

Rank	Industry	Entry rate*
1	Gypsum	0.93
2	Mineral water	0.55
3	Firefighting equipment	0.50
4	Motorcycles/rickshaws	0.50
5	Radios/TVs	0.50
6	Welding electrodes	0.50
7	Zips	0.50
8	Knitted textiles	0.45
9	Embroidery	0.43
10	Cones	0.43
11	Doubling of yarn	0.41
12	Powder coating	0.33
13	Pesticides and insecticides	0.32
14	Citrus grading	0.29
15	Fruit juices	0.29
16	Readymade garments	0.28
17	Gas appliances	0.28
18	Textile made-ups	0.28
19	Ceramics	0.28
20	Fertilizer	0.27

Note: Entry rate in industry i = number of new firms in industry i in 2006 that did not exist in 2002 divided by the total number of firms in industry i in 2006

Source: Government of the Punjab, Directory of Industries for 2006.

Table 3: Top 20 industries with the highest exit rates in Punjab, 2006

Rank	Industry	Exit rate*
1	Bus bodies	0.99
2	Nuts and bolts	0.97
3	Spices	0.95
4	Electroplating	0.89
5	Electric furnaces	0.88
6	Bakery products	0.85
7	Photographic goods	0.83
8	Razors/safety razors/blades	0.83
9	Dies and blocks	0.80
10	Knitted textiles	0.79
11	Ice cream	0.79
12	Zinc sulfate	0.75
13	Bicycles	0.75
14	Hand tools	0.67
15	Bulbs and tubes	0.67
16	Refineries	0.67
17	Unani medicines	0.67
18	Weights and scales	0.66
19	Agricultural implements	0.64
20	Pins/clips	0.60

Note: Exit rate in industry *i* = number of firms in industry *i* in 2002 that did not exist in 2006, divided by the total number of firms in industry *i* in 2002
Source: Government of the Punjab, Directory of Industries for 2006.

Table 4: Top 20 most agglomerated industries in Punjab, 2006

Rank	Industry	EGI*
1	Electroplating	1.5948
2	Citrus grading	1.1967
3	Wool scouring	1.1652
4	Powder coating	1.1072
5	Musical instruments	1.0586
6	Weights and scales	1.0529
7	Sports goods	1.0333
8	Leather garments	0.9820
9	Surgical instruments	0.9380
10	Utensils (all sorts)	0.9254
11	Belts	0.9214
12	Canvas shoes	0.8583
13	Raising cloth	0.8529
14	Cutlery	0.8209
15	Fiber tops	0.8169
16	Polyester yarn	0.8091
17	Crown corks	0.7284
18	Fiberglass	0.7151
19	Sanitary fittings	0.7131
20	Machine tools	0.7128

Note: EGI in 2002, measured using employment data.
Source: Government of the Punjab, Directory of Industries for 2006.

5. Firm Clustering and Dispersion in Punjab: An Aerial View

The notion that new firms are likely to locate near similar firms, thus leading to the formation of industrial clusters, can be illustrated using maps. In the first such exercise carried out for Punjab, this study maps eight industries, both clustered and dispersed, using the firm addresses given in the Directory of Industries for 2010.

The number of industrial clusters that have formed in specific areas of Punjab make it easier for incumbent as well as new firms to gain access to resources and technology. On the other hand, we can see that certain industries are completely dispersed and do not comply with the spatial concentration hypothesis presented in the literature. The industries mapped in Figures 1–4 exist as clusters because they require specialized inputs. Those mapped in Figures 5–8 represent industries that are highly dispersed in Punjab.

Figures 1–4: Examples of clustered industries

Figure 1: Rubber

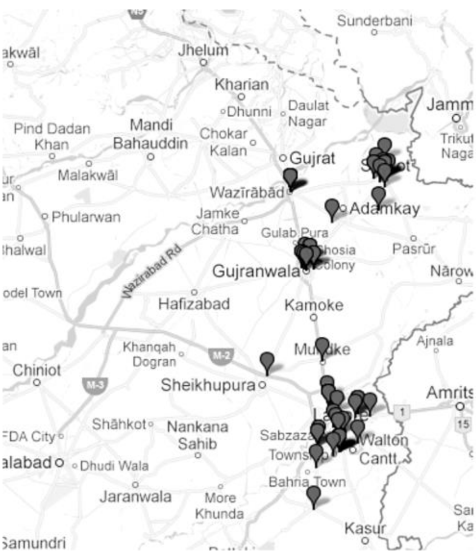


Figure 2: Surgical instruments

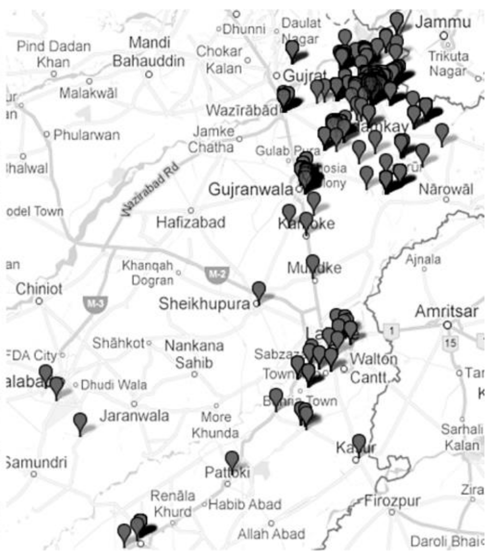


Figure 3: Sports goods

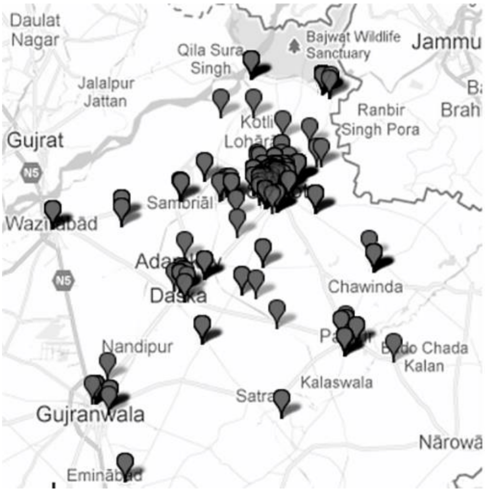
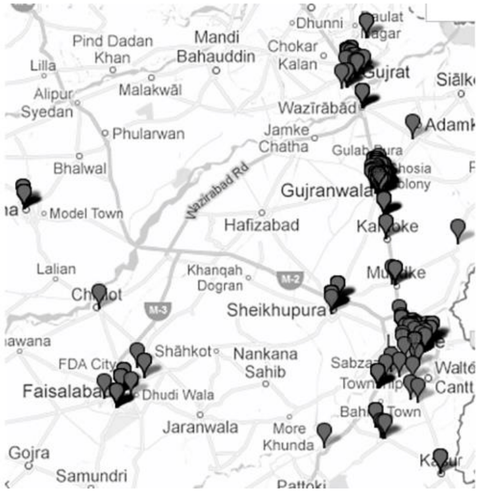


Figure 4: Iron and steel



Source: Based on data from Government of the Punjab, Directory of Industries for 2010.

Figures 5–8: Examples of dispersed industries

Figure 5: Sugar

Figure 6: Cement

Figure 7: Cotton

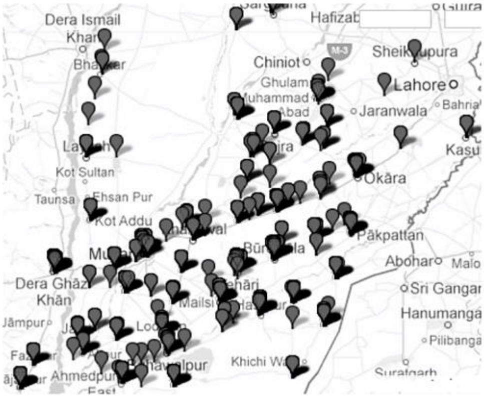
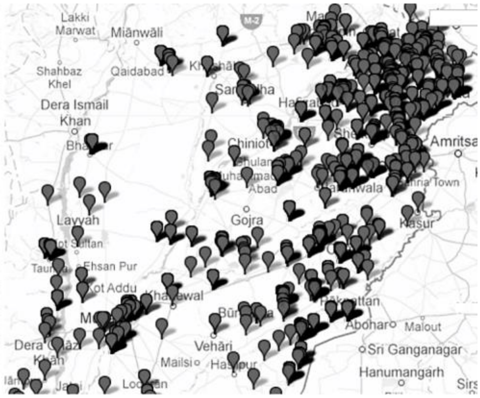


Figure 8: Rice



Source: Based on data from Government of the Punjab, Directory of Industries for 2010.

6. Agglomeration, Firm Entry and Exit: An Econometric Model

This paper's econometric model is designed to gauge the impact of agglomeration on firm entry and exit while controlling for other industry-level factors that affect entry and exit. Table 5 defines the variables used and indicates their hypothesized signs.

Table 5: Variables and definitions

Explanatory variable	Definition
EGI	The EGI of agglomeration is constructed using firm employment and consists of the Gini coefficient and Herfindahl index.
Firm age	The average age of a firm in an industry (how long since it was established).
Firm size	The average size of a firm in an industry, measured by its number of employees.
Output growth	The change in output during the study period.
Sunk cost	The average initial investment of firms in an industry.

The model below, which is adapted from other studies on firm turnover and agglomeration,[1] estimates the entry of new firms and the exit of existing ones against the agglomeration index while controlling for other factors that affect firm entry and exit. This cross-sectional analysis includes all 180 industries in Punjab for 2005/06. The equation is as follows:

$$E_i = \frac{N_i}{I_i} = \beta_0 + \beta_1 EGI_i + \beta_2 X_i + \varepsilon_i \qquad (11)$$

[1] See, for example, Devereux et al. (2004); Dumais et al. (2002); Carlton (1983).

E_i is the entry rate for industry i and is equal to the number of new firms in industry i in 2006 that did not exist in 2002 (N_i), divided by the total number of firms in industry i in 2006 (I_i). EGI_i is the agglomeration index for industry i in 2002 and X is a vector of control variables, including average firm size, average firm age, average sunk cost and output growth. To measure the entry rate, we compare the datasets for two years, where firms listed in the 2006 dataset but not in the 2002 dataset are considered new entrants. The subscript i refers to the 180 industries that comprise Punjab's manufacturing sector.

$$Z_i = \frac{M_i}{F_i} = \beta_0 + \beta_1 EGI_i + \beta_2 X_i + \varepsilon_i \tag{12}$$

Z_i is the exit rate for industry i and is equal to the number of firms in industry i in 2002 that did not exist in 2006 (M_i), divided by the total number of firms in industry i in 2002 (F_i). EGI_i is the agglomeration index for industry i in 2002 and X is a vector of control variables, including firm size, firm age, sunk cost and output growth. The exit rate is determined by comparing the two datasets: firms listed in the 2002 dataset but not in the 2006 dataset are considered to have exited the industry. The exit rate, therefore, represents those firms that have exited the industry as a proportion of the total firms in that industry in 2002.

Among the vector of control variables for both regression equations above, average firm size is measured using the employment data for the industry; firm age is based on the year in which it was set up. The output growth variable measures the change in output for the industry between 2002 and 2006. The higher the value of the EGI index, the more concentrated the industry is likely to be. The index for an industry i is:

$$EGI_i = \gamma_i = \frac{G - \left(1 - \sum_j X_j^2\right) H_i}{\left(1 - \sum_j X_j^2\right)(1 - H_i)} \tag{13}$$

G is the Gini coefficient, denoted by $\sum_j \left(S_{ij} - X_j\right)^2$. X_j is the share of employment for district j relative to total employment in Punjab. S_{ij} is the share of employment for district j in industry i relative to total employment in industry i in Punjab. H_i is the Herfindahl index for industry i, denoted by $\sum_k Z_k^2$ and Z_k is the kth firm's share of industry employment.

Both the Gini coefficient (G) and Herfindahl index (H) are useful measures per se. While the Gini coefficient measures income inequality across a population, as part of the EGI (γ) it represents raw geographical concentration. The equations above show that it has a positive impact on agglomeration: a rise in G will lead to a rise in γ. Intuitively, the more firms that are set up in a locale, the more agglomerated that industry is likely to be. The Herfindahl index is a measure of industry concentration and a rough indicator of the industry's market structure. It is negatively related to the agglomeration index according to the specification above, implying that a higher value of H is obtained when there are fewer firms in the industry. This translates into lower agglomeration. Conversely, a lower value of H is associated with a larger number of firms in the industry and thus with greater agglomeration.

7. Results and Discussion

This section uses ordinary least squares (OLS robust regression) to calculate the regression coefficients in both the entry and exit analyses.

7.1. Estimates of Firm Entry, Exit and Agglomeration

The study's estimates of firm entry and exit rates in Punjab's manufacturing sector from 2002 to 2006, as affected by agglomeration, imply that spillover benefits arise from geographical and industrial concentration. The results support the argument put forward by the literature: that agglomeration has a significant impact on firms' entry and exit rates and that the two are likely to be correlated.[2]

Firms tend to locate near similar units or in clusters to take advantage of spillovers in the form of access to technology, knowledge sharing and a labor supply with the required skills. The results also suggest that exit rates are higher in the more agglomerated industries: in the face of intense competition among firms, weaker firms find it difficult to survive as the incumbent firms start taking advantage of higher spillover benefits.

Table 6 presents the OLS results of the entry agglomeration and exit agglomeration analysis. The first two columns give the firm entry and agglomeration analysis coefficients, where column 2 controls for the effects of large industries (in terms of size) by incorporating industry dummies (excluded in column 1). A large industries dummy was created for those sectors with a large number of firms e.g. cotton industry with

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[2] See Devereux et al. (2004); Dumais et al. (2002); Carlton (1983); Rosenthal and Strange (2010); De Silva and McComb (2011) as discussed in Section 2.

over 1300 firms and rice industry with over 1700 firms to incorporate industry shocks.[3] The firm entry variable is the ratio of new firms (that entered the industry between 2002 and 2006) to the total number of firms in 2006. As shown in column 2, the EGI is positive and significant, implying that more firms will enter highly agglomerated industries than those that are dispersed, holding other industry factors constant.

Table 6: Regression results for entry agglomeration and exit agglomeration

	Entry		Exit	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
EGI	0.007	0.016**	-0.015	0.036**
	(0.0089)	(0.006)	(0.026)	(0.018)
Output growth	0.003	0.009***	0.002	-0.005
	(0.0023)	(0.002)	(0.007)	(0.005)
Firm age	-0.003***	-0.001*	0.002	0.003***
	(0.0007)	(0.003)	(0.001)	(0.001)
High cost (dummy = 1 if sunk cost > PRs50 m)	0.002 (0.0219)	0.036 (0.022)	0.027 (0.063)	0.028 (0.066)
Firm size: small (dummy = 1 if < 49 employees)	-0.011 (0.024)	-0.002 (0.024)	0.083 (0.068)	-0.028 (0.072)
Firm size: medium (dummy = 1 if ≥ 49 & < 100 employees)	0.030 (0.026)	0.015 (0.025)	0.064 (0.074)	-0.085 (0.072)
Firm size: large (dummy = 1 if ≥ 100 employees)	–	–	–	–
Large industries dummy	No	Yes	No	Yes
Cons.	0.129***	0.044*	0.118*	0.081
	(0.026)	(0.024)	(0.070)	(0.070)
N	N = 180	N = 180	N = 180	N = 180
R^2	R^2 = 0.08	R^2= 0.46	R^2 = 0.02	R^2 = 0.44

Note: *** = statistically significant at the 1 percent level, ** = statistically significant at the 5 percent level, * = statistically significant at the 10 percent level. Robust standard errors given in parentheses.
Source: Author's calculations.

The exit agglomeration results are also separated into those without and with industry dummies in columns 3 and 4, respectively. The exit rate is the ratio of firms that were operational in 2002 but not in

[3] Other large industries include surgical instruments, sports, tanneries, hosiery, foundry, flour, cold storage, auto-parts and agricultural implements.

2006 to the total number of firms in 2002. Column 4 shows that firm exit is positively influenced by the EGI, confirming that units are more likely to shut down in highly agglomerated industries.

This finding can be interpreted further by considering the impact of the EGI's components: the Gini coefficient and the Herfindahl index. Since both measure the concentration of firms, the more firms present either geographically or within an industry, the more competitive it is likely to be, thus making it difficult for existing firms to survive. If firms associate highly agglomerated industries with greater spillover benefits, then intuitively the latter will attract more entrants. However, these may also include weaker firms, which would have a higher probability of exiting the industry.

Among the control factors, output growth has a direct impact on the entry of new firms – this result holds only when the large industries dummy is controlled for. Industries with higher output growth will be more attractive to new firms hoping to achieve higher output and, in turn, higher profits. Another factor with a significant impact on firm entry is firm age, which has a negative impact on firm entry and a positive one on firm exit. The higher the number of older firms in an industry, the less likely new firms will enter or the more likely firms will exit, holding other factors constant. Older, more established firms tend to have stronger networks and the advantage of customer loyalty, thus creating barriers to entry for new firms or making it difficult for weaker firms to survive. Finally, the results show that the high cost and firm size variables have no significant impact on either entry or exit, although other studies have found them to affect firm entry and exit significantly.

7.2. Data Limitations and Avenues for Further Research

Since the Directory of Industries for Punjab is not published annually, the entry and exit analysis was restricted to five-year-interval (rather than annual) estimations. Any inaccurate records of firm names and addresses introduces the possibility of understating or overstating entry and exit rates (the names of some firms may have been spelled differently across datasets, thus affecting their likelihood of being included as an entrant or exiting firm). This problem was minimized by matching each firm to its year of establishment. The lack of information on firm sales, use of technology and leverage also limits the use of control variables in the estimations. Finally, this paper only incorporates industries in Punjab and could be extended to other provinces if similar data were available.

8. Conclusion

This paper contributes to the industrial organization literature on Pakistan by looking at the domestic factors affecting firm turnover in Punjab. New firms are attracted to industries characterized by agglomeration economies in the form of human and capital spillover benefits. Furthermore, firm entry tends to occur in industries with higher rates of output growth because this gives new establishments the chance to grow. The results also suggest that new firms are hesitant to enter industries dominated by older firms, which may prevent entrants from building a larger market share. The exit rate is also higher in such industries as weaker firms find it more difficult to survive.

The study provides some insight into industrial policies on promoting clusters where firms are highly integrated and resource and technological flows help them improve their productivity and growth. Industries are more likely to grow together while promoting competition among firms if they are more agglomerated.

References

Burki, A. A, & Khan, M. A. (2010, December). *Spatial inequality and geographic concentration of manufacturing industries in Pakistan*. Paper presented at the 26th Annual General Meeting and Conference of the Pakistan Society of Development Economists, Islamabad.

Carlton, D. W. (1983). The location and employment choices of new firms: An econometric model with discrete and continuous endogenous variables. *Review of Economics and Statistics*, *65*(3), 440–449.

De Silva, D. G., & McComb, R. P. (2011). *Geographical concentration and firm survival* (Working Paper No. 32906). Munich, Germany: University Library of Munich.

Devereux, M. P., Griffith, R., & Simpson, H. (2004). The geographic distribution of production activity in the UK. *Regional Science and Urban Economics*, *34*(5), 533–564.

Dumais, G., Ellison, G., & Glaeser, E. L. (2002). Geographic concentration as a dynamic process. *Review of Economics and Statistics*, *84*(2), 193–204.

Ellison, G., & Glaeser, E. L. (1997). Geographic concentration in US manufacturing industries: A dartboard approach. *Journal of Political Economy*, *105*(51), 889–927.

Fritsch, M., & Mueller, P. (2004). The effects of new business formation on regional development over time. *Regional Studies*, *38*(8), 961–976.

Hopenhayn, H. A. (1992). Entry, exit and firm dynamics in long-run equilibrium. *Econometrica*, *60*(5), 1127–1150.

Marshall, A. (1920). *Principles of economics* (8th ed.). London: Macmillan.

Porter, M. E. (2000). Locations, clusters, and company strategy. In G. L. Clark, M. P. Feldman & M. S. Gertler (Eds.), *The Oxford handbook of economic geography* (pp. 253–274). Oxford: Oxford University Press.

Roberts, B. M., & Thompson, S. (2003). Entry and exit in a transition economy: The case of Poland. *Review of Industrial Organization*, *22*(3), 225–243.

Rosenthal, S. S., & Strange, W. C. (2010). Small establishments/big effects: Agglomeration, industrial organization and entrepreneurship. In E. Glaeser (Ed.), *Agglomeration economics* (pp. 277–302). Chicago, IL: University of Chicago Press.

Soubeyran, A., & Thisse, J. F. (1998). Learning-by-doing and the development of industrial districts. *Journal of Urban Economics*, *45*(1), 156–176.

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Corporate Financial Leverage, Asset Utilization and Nonperforming Loans in Pakistan

Ijaz Hussain*

Abstract

This study applies panel least squares and fixed effects to a sample of 40 banks for the period 2006–14 to identify the key determinants of nonperforming loans (NPLs) in Pakistan. The findings suggest that, in addition to some macroeconomic and bank-specific variables, the corporate debt–equity ratio and financial burden have a positive, significant impact on NPLs, while corporate asset utilization and the diversification of bank activities significantly reduce the volume of NPLs. This has policy implications not only for the federal government, but also for bank managers, regulators and policy advisors.

Keywords: nonperforming loans, bank asset quality, diversification, Pakistan.

JEL classification: G00, G21, G28.

1. An Overview of Nonperforming Loans in Pakistan

Although the volume of nonperforming loans (NPLs) as a share of gross advances in Pakistan has declined from a peak of 16.2 percent in 2011, this ratio remains higher than the regional and world averages – 12.5 percent in 2014 compared to 7.0 percent for South Asia and 4.5 percent globally (Figures 1 and 2). The State Bank of Pakistan reveals that lending to the corporate sector alone accounts for almost 65.6 percent of gross advances for investment in noncurrent assets, working capital and trade financing. The corporate sector's contribution to the total volume of NPLs was alarmingly high at almost 70 percent in 2014 (Table 1). More than 94 percent of all bank credit is channeled to urban areas. The share of rural areas has never been more than 6 percent (Table 2).

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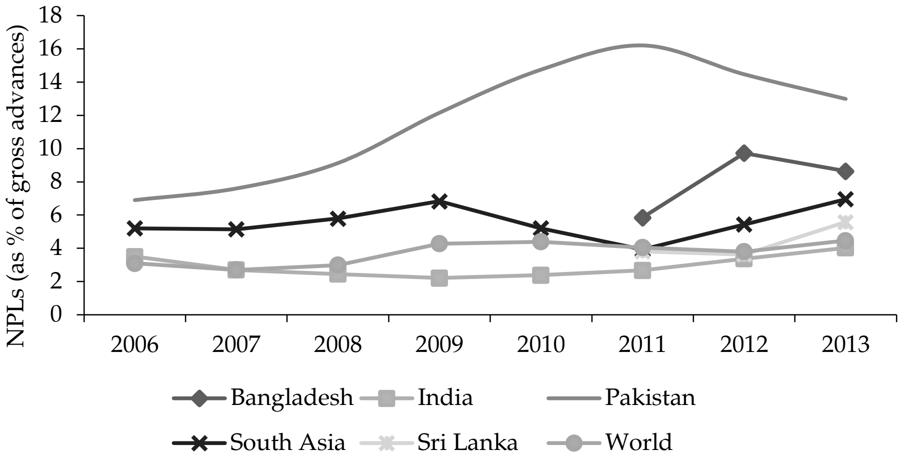
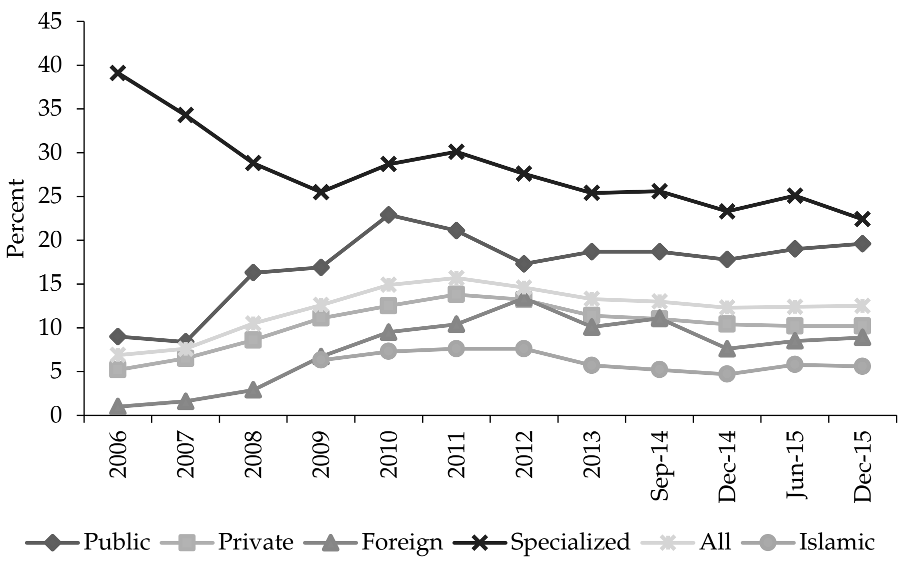
Figure 1: NPLs as a percentage of gross advances for selected South Asian countries and regional aggregates



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

Figure 2: NPLs as a percentage of gross advances, by bank type



Source: Author's calculations based on data from the State Bank of Pakistan.

Table 1: Distribution of NPLs, by finance segment, 2014

	Gross advances		NPLs	
Segment	PRs billion	% Share	PRs billion	% Share
Corporate	3,060.2	65.6	415.8	69.9
SME	264.5	5.7	89.7	15.1
Agriculture	245.6	5.3	36.4	6.1
Consumer	288.2	6.2	35.8	6.0
Commodity	570.8	12.2	4.6	0.8
Other	145.9	3.1	11.6	2.0
Total	4,661.8	100.0	595.3	100.0

Source: Author's calculations based on data from the State Bank of Pakistan.

Table 2: Distribution of bank credit, by area and segment, June 2015

Segment	**Rural**	**Urban**	**Total**
Trust	0.6%	99.4%	100.0%
Other	5.0%	95.0%	100.0%
NBFC	0.0%	100.0%	100.0%
Personal	10.8%	89.2%	100.0%
NFPSE	0.0%	100.0%	100.0%
Government	0.0%	100.0%	100.0%
Private sector	5.6%	94.4%	100.0%
Foreign	0.0%	0.0%	0.0%
Total	4.6%	95.4%	100.0%

Note: NBFC = nonbanking financial company, NFPSE = nonfinancial public sector enterprise.
Source: Author's calculations based on data from the State Bank of Pakistan.

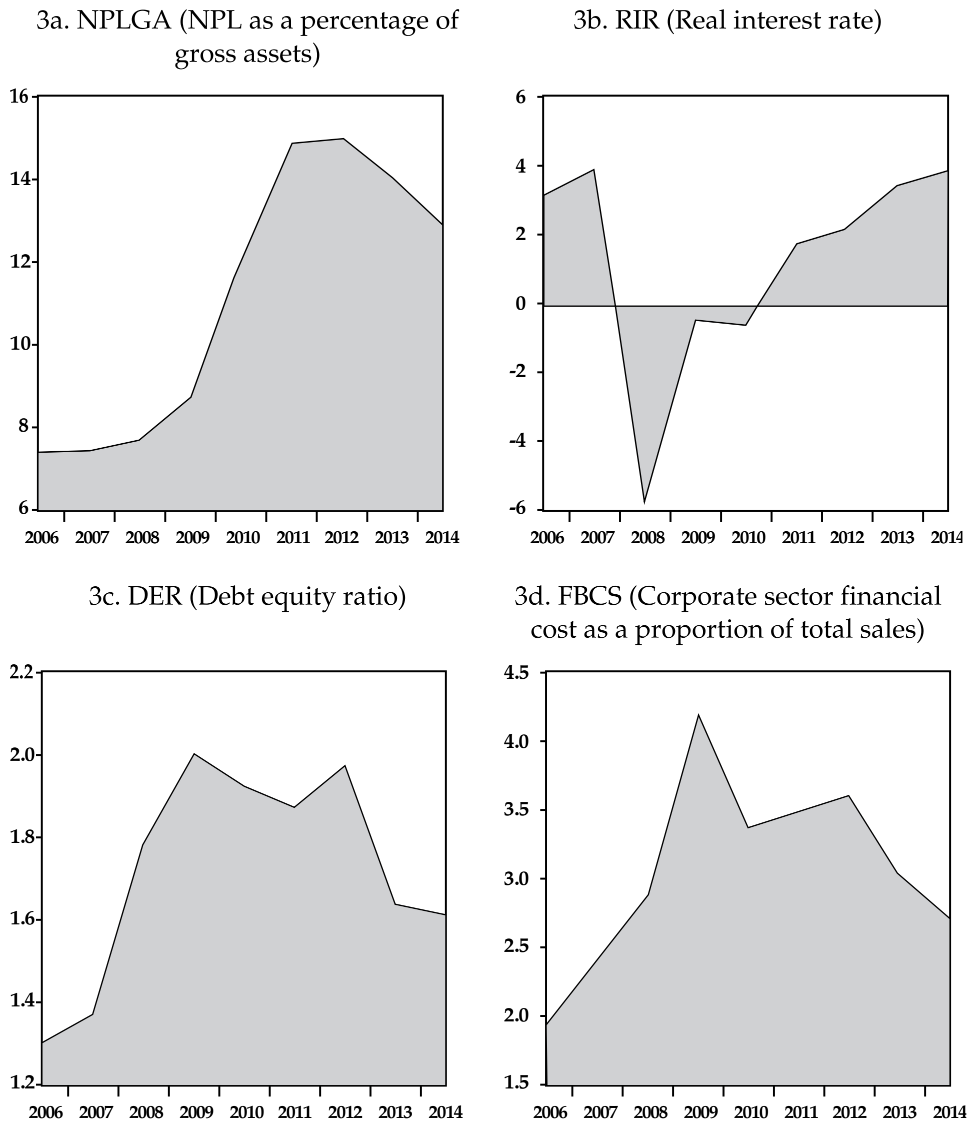
Motivated by the negative or very low real interest rate (RIR), which has never exceeded 4 percent, the nonfinancial corporate sector has borrowed on a large scale, significantly raising its debt–equity ratio (DER) and financial burden during the period 2006–10. This borrowing was used to expand the asset base – primarily noncurrent assets such as machinery and equipment – and to invest in speculative or nonproductive assets such as real estate (see Figure A1 in the Appendix).[1]

However, several factors have led to a sharp decline in asset turnover (corporate asset utilization), especially during 2006–10 (Figures 3a–h). These include severe energy shortfalls (Pakistan having been unable to expand its capacity to generate enough electricity and gas), expansions in the asset base,

[1] There is evidence that some cash-rich companies or groups of companies were even able to develop housing societies during this period.

the global financial crisis, an adverse local macroeconomic environment, and poor law and order.[2]

Figure 3: NPLs and selected corporate (nonfinancial) sector and macroeconomic indicators



3a. NPLGA (NPL as a percentage of gross assets)

3b. RIR (Real interest rate)

3c. DER (Debt equity ratio)

3d. FBCS (Corporate sector financial cost as a proportion of total sales)

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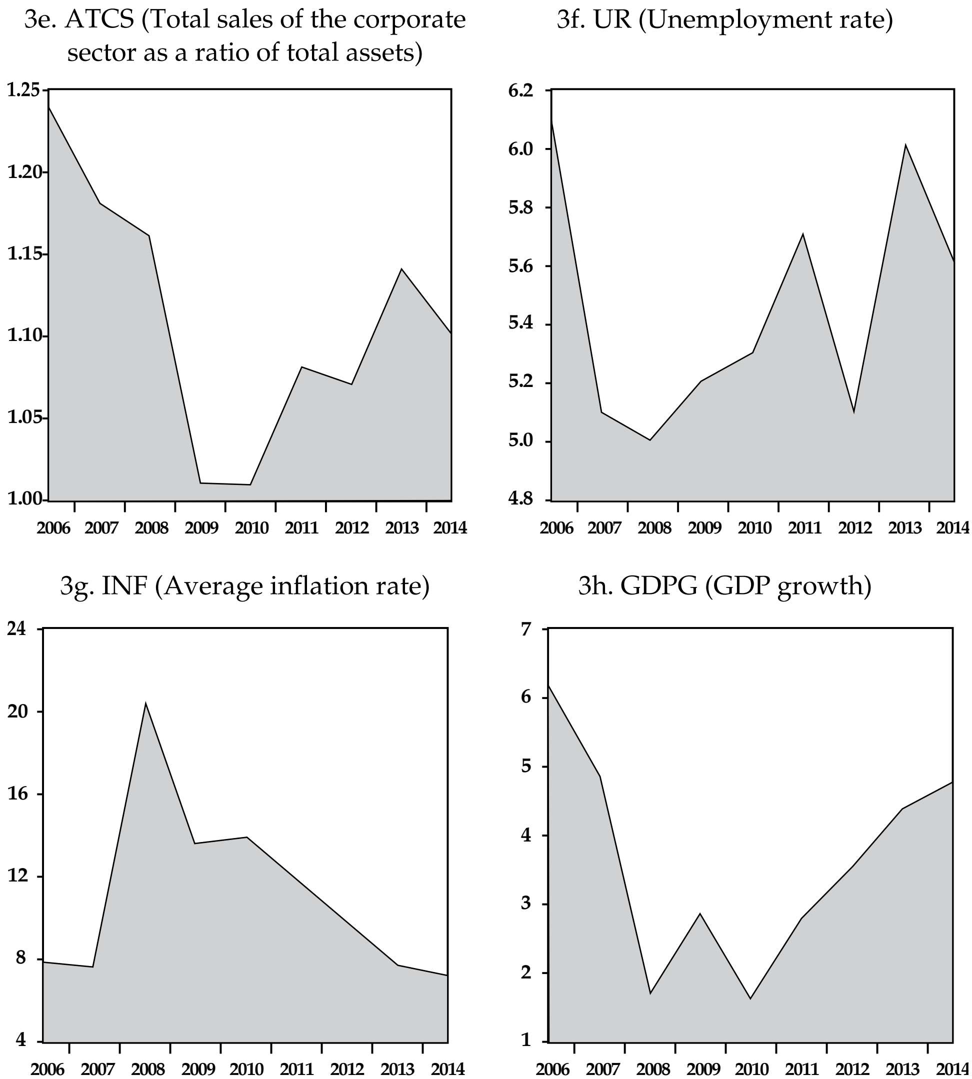
[2] Asset turnover ratio = corporate sector sales / total assets of corporate sector.



Source: Author's calculations based on data from the State Bank of Pakistan and Ministry of Finance, Government of Pakistan.

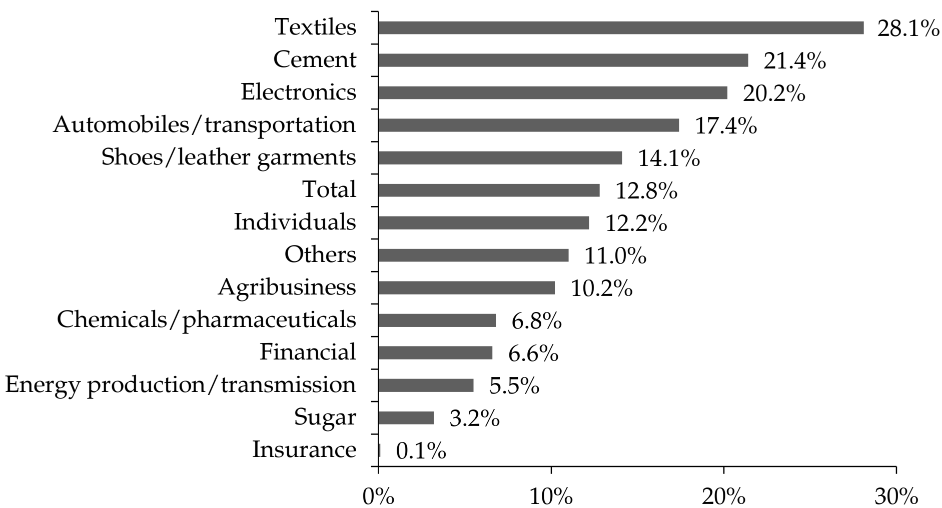
The corporate sector's noncurrent and total assets increased at a cumulative growth rate of 23.2 and 19.0 percent, respectively, while sales grew by only 13.0 percent during this period (Table 3). Greater financial leverage in terms of a larger financial burden and poor asset utilization has caused average bank asset quality to deteriorate, resulting in a sharp rise in NPLs, especially during 2006–10. Figure 4 shows that textiles, cement, electronics, automobiles and shoes/leather garments account for the highest NPLs. The incidence of loan defaulting in cement and automobiles – despite extensive construction activity and high demand for vehicles – is indicative of the moral hazard resulting from weak law enforcement in Pakistan.[3]

Table 3: Cumulative growth of various indicators

Indicator	2006–10	2011–14	2006–14
Sales	13.0%	10.2%	12.9%
Fixed assets	23.2%	9.9%	16.1%
Current assets	14.1%	8.5%	12.8%
Total assets	19.0%	9.3%	14.5%
Asset turnover	-5.0%	0.8%	-1.5%
Real GDP	2.7%	4.2%	3.3%

Source: Author's calculations based on data from the State Bank of Pakistan.

Figure 4: Infection ratio, by sector

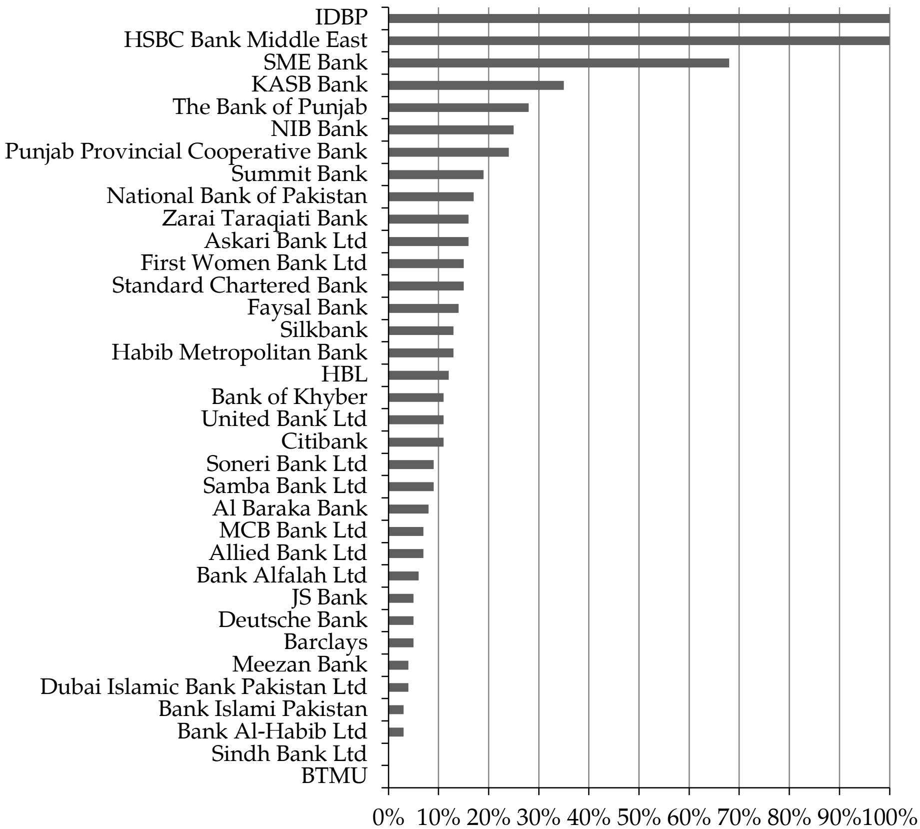


Source: Author's calculations based on data from the State Bank of Pakistan.

Figure 5 illustrates the gravity of the situation. For the Industrial Development Bank of Pakistan (IDBP) and HSBC Bank Middle East, NPLs account for 100 percent of gross advances. SME Bank and KASB Bank follow, with a corresponding share of 68 and 35 percent, respectively. The Bank of Punjab, NIB Bank and the Punjab Provincial Cooperative Bank account for 28, 25 and 24 percent. Clearly, specialized and public banks in Pakistan tend to have the highest NPL levels, while Islamic banks have among the lowest.

[3] Customers in Pakistan must wait three to six months for delivery after booking.

Figure 5: NPLs as a share of gross advances (individual banks), 2014

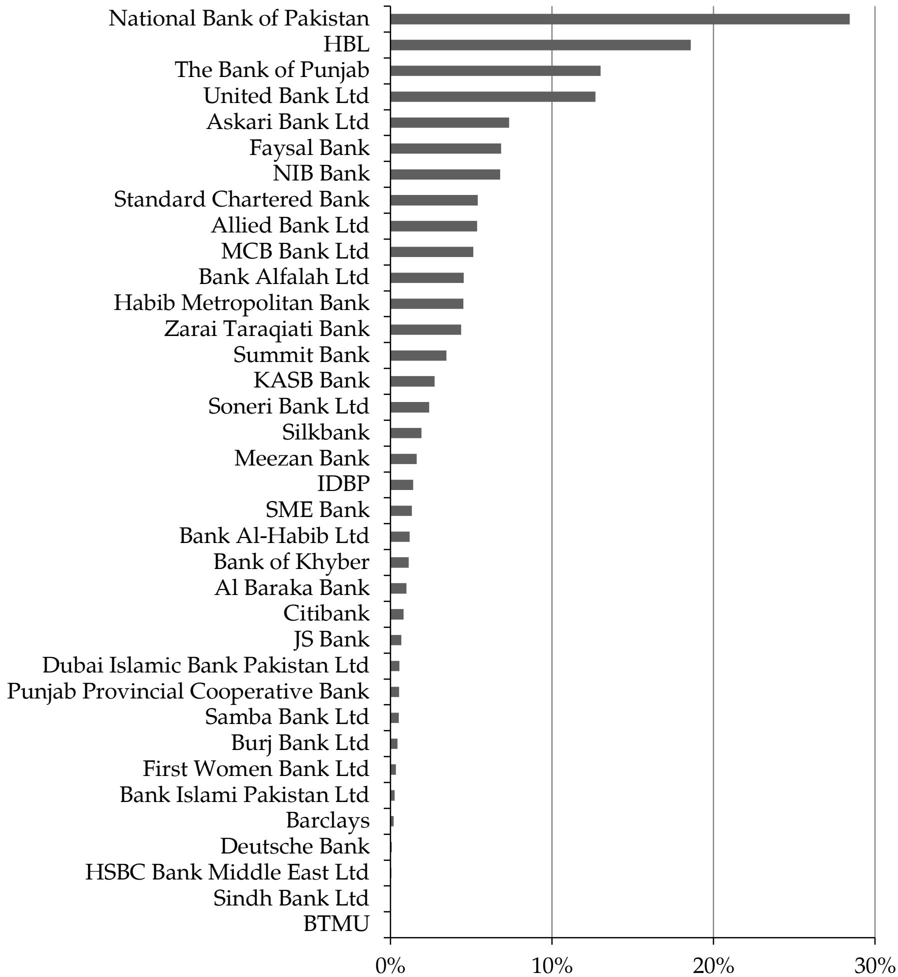


Source: Author's calculations based on data from the State Bank of Pakistan.

Larger banks appear to contribute more to the sector's total stock of NPLs than smaller banks (Figure 6). While Pakistan's macroeconomic recovery 2011 onward has improved the asset turnover of the corporate sector, this ratio is still far below its pre-2006 level. The NPL level has also fallen, but even this percentage is still excessive (see Figures 1–3).

A high NPL level can potentially deepen the severity and duration of a financial crisis and complicate macroeconomic management (Woo, 2000). It can also shatter investors' confidence in the banking system (Adhikary, 2006) and prevent economic recovery by cutting into profit margins and, therefore, the capital base for further lending (Bernanke & Lown, 1991). Combined with weak law enforcement, this is likely to drive out bona fide borrowers through a contagious financial malaise – 'bad' borrowers will have a negative impact on 'good' borrowers by inducing the latter to prolong their payments (Adhikary, 2006).

Figure 6: NPLs as a share of total NPLs (individual banks), 2014



Source: Author's calculations based on data from the State Bank of Pakistan.

Given that a bank's primary assets are its loans, it is important to evaluate asset quality to determine the financial health and efficiency of the banking sector (Islam, Karim & Islam, 2014). De Bock and Demyanets (2012) find that economic growth slows down and exchange rates depreciate in emerging markets characterized by very high NPL levels. This context explains the need to explore the key determinants of NPLs in Pakistan, a better understanding of which would help policymakers, corporate managers and regulators identify the sector's vulnerable points and formulate policies to control the high level of NPLs in the country.

In identifying the determinants of NPLs, the literature tends to neglect the role of aggregate corporate sector indicators and the diversification of bank activities. The study seeks to address this gap, using panel least squares and fixed effects (FE) to examine a sample of 40 banks in Pakistan for the period 2006–14. We find that bank-specific variables and corporate sector indicators explain the variation in NPLs better than the state of the macroeconomic environment.

The study's findings suggest that the concentration of the credit market, the lending rate, the cost of living, stock prices, bank size, public sector ownership, specialized banking, the DER and financial burden have a positive and significant impact on NPLs. Factors that significantly reduce NPLs include the diversification of bank activities, the scale of loan appraisal and monitoring systems, Islamic banking, corporate asset turnover and a favorable macroeconomic environment. Foreign banking and nominal exchange rate movements have an insignificant impact, given that bank lending to foreign borrowers is nil.

The remaining paper is organized as follows. Section 2 provides a comprehensive review of the literature on bank asset quality and its determinants. Sections 3–5 describe the study's dataset, methodology and research design. Section 6 presents the study's findings and Section 7 concludes the study with a set of policy implications.

2. A Review of the Literature

Çifter (2015) uses the generalized method of moments and instrumental variable approach to examine the short- and long-run effects of bank concentration on NPLs across 10 Central and Eastern European countries. The study employs a fully modified ordinary least squares (OLS) model and finds that bank concentration has an insignificant impact on NPLs both in the short run and long run. However, the individual fully modified OLS results reveal that bank concentration reduces NPLs in Estonia, Latvia and Slovakia, and increases NPLs in Bulgaria, Croatia, Lithuania, Poland and Slovenia in the long run.

Klein (2013) observes that macroeconomic conditions have greater explanatory power than bank-specific factors, with a strong feedback effect from NPLs to the real economy in Central, Eastern and Southeastern Europe over the period 1998–2011. The study suggests that unemployment, inflation and the exchange rate have a positive and significant effect on NPLs. Among bank-level variables, the capital ratio and returns on equity have a negative impact, while financial leverage has a positive impact on NPLs. Looking at consumer, business and mortgage loans separately, Louzis, Vouldis and Metaxas (2012) find that NPLs in Greece are determined chiefly by macro-fundamentals (GDP, the unemployment rate and interest rates) and management quality.

In a cross-country study of 75 countries, Beck, Jakubik and Piloiu (2015) identify GDP growth, the exchange rate, the lending interest rate and stock prices as the key macroeconomic determinants of NPLs. GDP growth is indicative of more employment opportunities and boosts economic activity, which in turn directly influences the ability of borrowers to repay their debt, thus reducing the volume of NPLs. Higher stock prices tend to lower housing prices, which reduces the quality of housing loans. Higher lending interest rates raise the cost of borrowing and, therefore, the likelihood of default or NPLs.

Using an FE model for a panel dataset, Khemraj and Pasha (2009) note that the real effective exchange rate, bank size, rapid credit growth and higher interest rates have a positive effect on NPLs. Boudriga, Taktak and Jellouli (2010) conclude that higher bank capitalization and prudent provisioning policy, private ownership, foreign participation and bank concentration reduce the volume of NPLs. Siddiqui, Malik and Shah (2012) find that interest rates are significantly – but not solely – responsible for NPLs in Pakistan. Based on a sample of Spanish banks, Salas and Saurina (2002) find that NPLs are influenced by individual bank-level variables such as bank size, the net interest margin, the capital ratio and market power in addition to real GDP growth. Beck, Demirgüç-Kunt and Merrouche (2013) suggest that Islamic bank stocks perform better than conventional stocks, based on their asset quality and capitalization.

Using bank-level data for a sample of 26 commercial banks over the period 2001–10, Hussain (2012) finds that previous NPLs, credit growth, interest margins, foreign and public sector bank ownership, corporate gearing, currency depreciation and the real cost of debt have a positive and significant impact on the volume of NPLs. Bank size and profitability, industrial growth and profitability, GDP growth and per capita income have a negative impact in this case. Finally, Glen and Mondragón-Vélez (2011) identify real GDP growth, private sector leverage and insufficient capitalization within the banking system as the key determinants of loan loss provision in 22 developing economies during 1996–2008.

Private sector enterprises borrow to expand their asset base. Debt repayment depends on a firm's ability to utilize these assets to increase its general sales or revenue (asset turnover) and reduce its financial burden (financial expenses as a percentage of sales) consequent to increased financial leverage. Despite the importance of asset turnover and financial burden as indicators of the corporate sector, they have received little attention in the literature. Both indicators are especially relevant in Pakistan's case, where 65.6 percent of total advances are channeled to the corporate sector alone, which accounts for almost 70 percent of the total volume of NPLs in the banking industry.

Unlike most other studies, this study controls for four types of banks (see below). It builds on Hussain (2012) and includes the following three categories of NPL determinants:

- *Bank or banking industry-specific factors*: credit market concentration (size and growth of loan portfolios), the diversification of bank activities, the lending rate of interest, bank size, bank capitalization, the size of the loan appraisal and monitoring system, bank ownership and bank type (with dummy variables representing Islamic versus conventional, public versus private, specialized versus nonspecialized and local versus foreign banks).
- *Macroeconomic indicators*: GDP growth, inflation, the exchange rate, stock prices, the real cost of debt (the RIR) and per capita income.
- *Corporate sector indicators*: capital structure or financial leverage, financial burden and asset utilization.

3. Datasets and Sample

We use bank-level data for the period 2006–14, drawing on the State Bank of Pakistan's balance sheet analyses of the financial sector (for 2009/10 and 2010–14) and periodically published banking statistics. The study's nonfinancial corporate sector data was obtained from the balance sheet analyses of nonfinancial companies listed on the Karachi Stock Exchange (2009/10 and 2010–14). The data on macroeconomic indicators is from the Pakistan Economic Survey and World Bank database.

The sample comprises all 40 banks operating in Pakistan, including private, public, Islamic, conventional, local, foreign, specialized and nonspecialized banks. The study covers the period 2006–14 for two reasons: (i) the low RIR regime that started in 2005 motivated firms to borrow large amounts, which increased their financial leverage; and (ii) asset utilization began to decline in 2006, largely due to the energy crisis and constant power outages, security concerns on account of increased militancy and the overall adverse macroeconomic environment.

4. Construction of Variables

This section describes each of the variables used.

4.1. Dependent Variable

The NPL rate is the dependent variable. To enable comparison across banks, countries and regional aggregates, we use the ratio of NPLs to gross advances as a proxy for NPLs:

$$NPLGA_{it} = \frac{NPL_{it}}{GA_{it}} * 100 \quad (1)$$

where $NPLGA_{it}$ represents NPLs as a percentage of gross advances, i denotes the cross-section (bank) and t denotes time. NPL_{it} is the volume of NPLs for bank i at the end of period t and GA_{it} denotes the gross advances of bank i at the end of period t.

4.2. Independent Variables

Bank concentration in the credit market. We use gross advances as a share of total assets as a proxy for the bank's concentration in the credit market:

$$CCM_{it} = \frac{GA_{it}}{TA_{it}} \quad (1)$$

CCM_{it} captures both the relative size and growth of the bank's loan portfolio. An increase in CCM_{it} over time is indicative of an increase in the size and growth of the lending portfolio.

Banks that lend to low-quality borrowers face higher NPL levels during periods of low interest or credit booms because their capacity to process loan applications is constrained (Berger & Udell, 2004; Fernández de Lis, Pagés & Saurina, 2001). Keeton (1999) and Kwan and Eisenbeis (1997) find that rapid credit growth leads to larger loan losses because banks that pursue credit growth (especially during the expansion phase of the business cycle) tend to lower their standards of loan appraisal. This, in turn, raises NPLs.

During episodes of low credit growth or a recession, NPL levels rise (Eisenbeis, 1997) because borrowers draw down their lines of equity and credit in addition to the decline in their business, which compels them to default. We expect CCM_{it} to have a positive coefficient: the larger the lending portfolio or the higher its growth rate, the more likely the incidence of NPLs (although the coefficient can also be negative).

An alternative measure is the simple growth rate of the lending portfolio (CG_{it}):

$$CG_{it} = \frac{\Delta GA_{it}}{GA_{it}} * 100$$

where ΔGA_{it} denotes the change in gross advances and GA_{it} the gross advances of bank *i* in period *t*.

Bank lending interest rate. The average lending interest rate charged by the bank on good or collectible advances is:

$$LIR_{it} = \frac{IR_{it}}{AN_{it}} * 100 \qquad (2)$$

where IR_{it} is the interest revenue earned and AN_{it} denotes good or collectible advances or loans. We use net advances instead of gross advances in equation (2) because banks earn interest revenue on collectible loans. Banks that earn higher interest revenue on good loans are more vulnerable to bad debts. Equally, NPLs increase with the interest rate because it raises the debt servicing cost of borrowers with floating rate contracts (Espinoza & Prasad, 2010; Kauko, 2012; Beck et al., 2015).

Here, the average lending interest rate (charged by an individual bank on its collectible loans) is different from the policy rate because the short-term policy rates set by the central bank are not transmitted fully to the lending interest rates (Beck et al., 2015).

Diversification of bank activities. Higher noninterest revenue is indicative of greater diversification in terms of bank activities other than borrowing and lending and is measured as follows:

$$DIV_{it} = \frac{NIR_{it}}{TA_{it}} * 100 \qquad (3)$$

where NIR_{it} represents the bank's noninterest revenue and TA_{it} its total assets. Greater diversification is likely to reduce the level of NPLs, but is rarely included as a determinant in the literature.

Size of loan appraisal and monitoring system. While administrative expenses are often used as a proxy for cost efficiency (see Berger & DeYoung, 1997; Podpiera & Weill, 2008), this study broadens the indicator by looking at the level and growth of a bank's administrative expenses to measure the size of its loan appraisal and monitoring system:

$$SAMS_{it} = \log(AE_{it}) \tag{4}$$

A larger loan appraisal and monitoring system is indicative of the bank's capacity for appraising and monitoring loan applications and is, therefore, likely to reduce the level of NPLs.

Bank capitalization. Bank capitalization is the ratio of stockholders' equity to the bank's total assets:

$$CR_{it} = \frac{SE_{it}}{TA_{it}} \tag{5}$$

where SE_{it} denotes shareholders' equity and TA_{it} the bank's total assets. Higher bank capitalization reduces NPLs as financially strong banks are less likely to invest in risky projects (Boudriga et al., 2010; Louzis et al., 2012; Klein, 2013).

Bank size. Bank size is measured as a bank's total assets in proportion to the banking industry's total assets:

$$BS_{it} = \frac{TA_{it}}{\sum_{i=1}^{n} TA_{it}} * 100 \tag{6}$$

where TA_{it} represents the total assets of bank $\underline{i}$ in period *t* while $\sum_{i=1}^{n} TA_{it}$ is the sum of total assets owned by *n* banks in period *t*.

Bank size is also indicative of a bank's market power, which may be associated with higher NPLs: larger banks are more likely to be interested in cornering a larger share of the market by investing in risky projects with a higher incidence of NPLs (Khemraj & Pasha, 2009). That said, larger banks are also likely to have better loan appraisal and monitoring systems in place, which would reduce their NPLs (Louzis et al., 2012; Salas & Saurina, 2002).

Bank type. We use dummy variables to control for NPLs across the four types of banks: D1 = 1 for public banks and 0 otherwise, D2 = 1 for Islamic banks and 0 otherwise, D3 = 1 for foreign banks and 0 otherwise, and D4 = 1 for specialized banks and 0 otherwise.

Corporate asset utilization. The asset turnover of the corporate sector is a proxy for corporate asset utilization, calculated as follows:

$$ATCS_t = \frac{SCS_t}{TACS_t} \tag{7}$$

where SCS_t denotes the total sales of the corporate sector and $TACS_t$ its total assets. Higher corporate asset utilization implies that the sector's ability to repay its loans is greater, which reduces the incidence of NPLs.

Corporate financial leverage. While there are different measures of financial leverage, including the gearing ratio, equity multiplier and debt ratio, we use the most common measure, the DER, as a proxy for financial leverage:

$$DER_t = \frac{TL_t}{SE_t} \tag{8}$$

where TL_t and SE_t represent the total liabilities and total stockholders' equity of the corporate sector. A higher DER is indicative of greater risk of default, which is likely to raise the NPL level.

Corporate financial burden. Financing costs, including interest expenses as a percentage of sales, are used as a proxy for the corporate sector's financial burden:

$$FBCS_t = \frac{FCCS_t}{SCS_t} * 100 \tag{9}$$

where $FCCS_t$ and SCS_t denote the sector's financing costs and total sales, respectively. A higher corporate financial burden increases the likelihood of default and the level of NPLs.

The financial burden can also be captured using the lending RIR or cost of borrowing as follows:

$$RIR_t = AIR_t - INF_t \tag{10}$$

where AIR_t and INF_t are the average lending interest rate and inflation rate, respectively. A higher RIR (the real cost of debt servicing) is likely to raise the probability of default and the NPL level.

Inflation. We use the consumer price index as a measure of inflation, which affects the ability of both individuals and institutions to repay their debts. Borrowers tend to benefit from a fixed rather than varying inflation rate, which implies that higher inflation can increase the NPL level (Klein, 2013). However, it may also improve loan repayment by making loans cheaper to repay (Anastasiou, Lourie & Tsionas, 2016), thus reducing the level of NPLs.

Macroeconomic environment. Real GDP growth, measured by *log* $(RGDP_t)$, and per capita income (PCI_t) are tested separately in alternative specifications to capture the effect of the macroeconomic environment on NPLs. The unemployment rate can also be used for this purpose (see Klein, 2013). An adverse macroeconomic environment is likely to raise NPLs and vice versa (Klein, 2013; Messai & Jouini, 2013; Beck et al., 2015; Anastasiou et al., 2016).

Nominal exchange rate. Movements in the nominal exchange rate NER_t capture the impact of global changes on NPLs. Depending on a country's foreign assets and liabilities, the nominal exchange rate can affect NPLs either positively or negatively (Klein, 2013; Beck et al., 2015). Exchange rates can also influence NPLs through trade finance (Beck et al., 2015).

Stock prices. The KSE-100 index $(KSEH_t)$ is used to measure stock price movements. Since stock prices are correlated with housing (and other asset) prices, they have an indirect impact on the value of collateral and, therefore, on the quality of loans (Beck et al., 2015).

Proportion of lending to the textiles sector. We control for the impact of the largest share of lending by using the percentage of bank lending to the textiles sector $(LPTS_t)$. This is likely to have a positive effect on potential defaults, given the sector's political influence.

Global financial crisis. The impact of the global financial crisis on NPLs is captured by a dummy variable (D5), where D5 = 1 for 2009 and 0 otherwise.

Share of bank lending to the corporate sector. We control for the impact of the share of bank lending to the corporate sector by introducing a dummy variable (D6), where D6 = 1 if the share of bank lending to this sector is 50 percent or higher in a given year and 0 otherwise.

5. Methodology

This study combines cross-section and time series data and uses panel least squares and FE regression models of the following standard forms, respectively:

$$NPLGA_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Y_t + \beta_3 Z_t + \alpha_i + \mu_t + \varepsilon_{it} \quad (1)$$

$$NPLGA_{it} = \beta_0 + \beta_1 X_{it} + \varepsilon_{it} \quad (2)$$

where $NPLGA_{it}$ denotes NPLs as a percentage of gross advances and i and t specify the cross-section and time, respectively. β_0, β_1, β_2 and β_3 are unknown constants. X_{it} is a set of bank-specific explanatory variables that vary across banks and time. Y_t and Z_t are vectors of macroeconomic and nonfinancial corporate sector-specific variables that vary over time only. α_i and μ_t denote cross-section and time effects (random or fixed), respectively, while ε_{it} is the error term.

The error term and its relationship with the explanatory variables in both models is very important. The use of OLS in equation (1) above assumes the absence of unobservable firm- and time-specific factors, while the FE model in equation (2) assumes that ε_{it} varies nonstochastically over i or t. This makes the model analogous to a dummy variable model in one dimension. The FE model also assumes that cross-sections have unique attributes that do not vary over time and are not a result of random variation. The model thus provides consistent estimates regardless of the correlation mentioned above.

6. Results and Discussion

Tables 4 and 5 present the study's descriptive statistics and a matrix of correlation coefficients, respectively. While there is evidence of very low correlation between the bank-specific variables and aggregate indicators of the nonfinancial corporate sector, there is relatively high correlation among the macroeconomic indicators and no evidence of perfect multicollinearity.

Table 6 gives the results of the cross-section and period FE models. Table 7 reports the results of the redundant FE tests (joint significance). The use of FE is justified because the cross-section and period effects are significant. Tables 8–10 present the regression results of the panel least squares model (for all banks and excluding specialized banks with an NPL level of 100 percent) and FE model.

Table 4: Descriptive statistics

	NPLGA	CCM	LIR	DIV	SAMS	CR	BS	D1	D2
Mean	0.17	0.52	0.35	0.00	14.62	0.06	0.03	0.25	0.13
Median	0.10	0.51	0.18	0.01	14.73	0.10	0.01	0.00	0.00
Max.	1.00	1.65	17.87	0.09	17.60	5.57	0.16	1.00	1.00
Min.	0.00	0.01	0.00	-0.22	6.91	-7.21	0.00	0.00	0.00
SD	0.21	0.22	1.40	0.03	1.56	1.00	0.04	0.43	0.34
Skewness	2.36	1.71	11.44	-2.51	-0.77	-3.20	1.97	1.15	2.21
Kurtosis	8.68	8.98	140.01	17.54	4.38	32.00	6.42	2.33	5.88
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	339	340	340	340	340	340	340	340	340

Source: Author's calculations based on data from the State Bank of Pakistan.

Table 5: Matrix of correlation coefficients

	NPLGA	CCM	LIR	DIV	SAMS	CR	BS	D1	D2	D3	D4	Log RGDP	NER	CPI	KSEH	RIR	ATCS (-1)	D (DER)
NPLGA	1.000	0.540	0.447	-0.270	-0.353	-0.491	-0.226	0.419	-0.207	-0.042	0.579	0.105	0.138	0.130	0.055	0.043	-0.165	-0.108
CCM	0.540	1.000	0.196	-0.164	-0.054	-0.521	-0.050	0.448	-0.103	-0.413	0.648	-0.116	-0.109	-0.121	-0.108	-0.145	0.064	0.107
LIR	0.447	0.196	1.000	0.125	-0.250	-0.451	-0.097	0.113	-0.051	0.084	0.216	0.128	0.116	0.116	0.124	0.064	-0.029	-0.095
DIV	-0.270	-0.164	0.125	1.000	0.273	-0.112	0.322	-0.010	-0.046	0.039	-0.012	0.137	0.083	0.128	0.158	0.185	-0.031	-0.136
SAMS	-0.353	-0.054	-0.250	0.273	1.000	0.230	0.730	-0.148	-0.086	-0.398	-0.258	0.185	0.195	0.195	0.135	0.082	-0.127	-0.118
CR	-0.491	-0.521	-0.451	-0.112	0.230	1.000	0.183	-0.200	0.038	0.119	-0.415	-0.081	-0.091	-0.089	-0.056	-0.029	0.073	0.060
BS	-0.226	-0.050	-0.097	0.322	0.730	0.183	1.000	-0.030	-0.198	-0.251	-0.219	0.012	0.008	0.012	0.012	0.015	-0.006	-0.012
D1	0.419	0.448	0.113	-0.010	-0.148	-0.200	-0.030	1.000	-0.223	-0.233	0.599	0.032	0.027	0.031	0.031	0.025	-0.006	-0.020
D2	-0.207	-0.103	-0.051	-0.046	-0.086	0.038	-0.198	-0.223	1.000	-0.156	-0.134	0.017	0.020	0.020	0.006	-0.004	-0.018	-0.005
D3	-0.042	-0.413	0.084	0.039	-0.398	0.119	-0.251	-0.233	-0.156	1.000	-0.139	-0.006	0.000	-0.004	-0.008	-0.004	-0.008	-0.001
D4	0.579	0.648	0.216	-0.012	-0.258	-0.415	-0.219	0.599	-0.134	-0.139	1.000	0.004	0.002	0.004	0.004	0.005	-0.001	-0.003
Log RGDP	0.105	-0.116	0.128	0.137	0.185	-0.081	0.012	0.032	0.017	-0.006	0.004	1.000	0.941	0.977	0.895	0.547	-0.388	-0.619
NER	0.138	-0.109	0.116	0.083	0.195	-0.091	0.008	0.027	0.020	0.000	0.002	0.941	1.000	0.975	0.725	0.402	-0.598	-0.623
CPI	0.130	-0.121	0.116	0.128	0.195	-0.089	0.012	0.031	0.020	-0.004	0.004	0.977	0.975	1.000	0.795	0.484	-0.558	-0.626
KSEH	0.055	-0.108	0.124	0.158	0.135	-0.056	0.012	0.031	0.006	-0.008	0.004	0.895	0.725	0.795	1.000	0.731	-0.072	-0.642
RIR	0.043	-0.145	0.064	0.185	0.082	-0.029	0.015	0.025	-0.004	-0.004	0.005	0.547	0.402	0.484	0.731	1.000	-0.069	-0.712
ATCS (-1)	-0.165	0.064	-0.029	-0.031	-0.127	0.073	-0.006	-0.006	-0.018	-0.008	-0.001	-0.388	-0.598	-0.558	-0.072	-0.069	1.000	0.561
D (DER)	-0.108	0.107	-0.095	-0.136	-0.118	0.060	-0.012	-0.020	-0.005	-0.001	-0.003	-0.619	-0.623	-0.626	-0.642	-0.712	0.561	1.000

Source: Author's calculations.

Table 6: Evidence of FE

Cross-section FE			Period FE		
	CROSSID	Effect		DATEID	Effect
1	1	-0.1460	1	1/1/2007	-0.0660
2	2	0.0041	2	1/1/2008	-0.0450
3	3	-0.0290	3	1/1/2009	-0.0150
4	4	-0.0240	4	1/1/2010	0.0378
5	5	-0.1260	5	1/1/2011	0.0250
6	6	-0.2460	6	1/1/2012	0.0335
7	7	0.0490	7	1/1/2013	0.0166
8	8	0.0340	8	1/1/2014	0.0131
9	9	-0.0980			
10	10	-0.0430			
11	11	0.0072			
12	12	-0.1290			
13	13	0.0271			
14	14	0.1509			
15	15	-0.0090			
16	16	-0.0880			
17	17	0.0184			
18	18	0.0801			
19	19	0.0544			
20	20	0.0889			
21	21	-0.0750			
22	22	0.0028			
23	23	-0.0360			
24	24	0.0810			
25	25	-0.0570			
26	26	0.1246			
27	27	-0.1520			
28	28	0.1816			
29	29	-0.0450			
30	30	0.0975			
31	31	-0.1580			
32	32	0.1250			
33	33	0.0994			
34	34	0.0628			
35	35	0.2623			
36	36	0.0856			
37	37	-0.1020			
38	38	-0.1430			
39	39	-0.1050			
40	40	-0.0450			

Source: Author's calculations.

Table 7: Redundant FE test results

Effects test	Statistic	df	Prob.
Cross-section FE	2.05	(39,245)	0.0000
Cross-section chi-square	84.39	39	0.0000
Period FE	3.83	(7,245)	0.0000
Period chi-square	31.08	7	0.0000
Cross-section/period FE	2.12	(46,245)	0.0000
Cross-section/period chi-square	100.39	46	0.0000

Source: Author's calculations.

Banks' concentration in the credit market (or credit growth) has a significant and positive coefficient.[4] The positive coefficient is consistent with the findings of Berger and Udell (2004), Fernández de Lis et al. (2001), Keeton (1999) and Kwan and Eisenbeis (1997).

The lending interest rate has a positive, significant (at 1 percent across all specifications) impact on NPLs. The coefficient is stable and theoretically consistent with the findings of Espinoza and Prasad (2010), Kauko (2012) and Beck et al. (2015).

The diversification variable has a significant (at 1 percent across all specifications) and negative impact on NPLs. The sign of the coefficient is as expected.

Banks that offer their employees attractive remuneration (the growth of employee incentives) or spend more on loan appraisals are in a better position to control and monitor credit provision, which significantly reduces their NPLs (excluding specifications 9 and 10).

The negative and significant (at 5 percent) coefficient of the capitalization ratio signifies that financially strong, stable banks avoid risky lending and thus have relatively low NPL levels. This finding is consistent with Boudriga et al. (2010), Louzis et al. (2012) and Klein (2013).

Bank size has a positive and significant coefficient (at a 5 percent confidence level) in most specifications with a stable magnitude, excluding specifications 6–9. This finding is consistent with Khemraj and Pasha (2009), but contradicts Louzis et al. (2012) and Salas and Saurina (2002). The hypothesis that larger banks are more inclined to undertake risky lending holds, therefore, in Pakistan's case.

[4] At a 1 percent confidence level, excluding specifications 10 and 11 where it is significant at 5 percent.

Table 8: Regression results: panel least squares (all banks)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
C	-0.089	-0.076	-0.049	0.246	0.241	0.287	0.214	0.224	0.184	0.219	1.022	1.036	1.177	1.066	1.066	1.053	68.976	1.284	116.687	2.774	0.873
	0.000	0.011	0.168	0.016	0.011	0.033	0.099	0.080	0.092	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CCM	0.498	0.438	0.387	0.404	0.334	0.334	0.229	0.225	0.237	0.102	0.137	0.169	0.175	0.184	0.184	0.183	0.186	0.186	0.185	0.186	0.186
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.018	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
LIR		0.051	0.057	0.051	0.043	0.043	0.043	0.042	0.042	0.041	0.037	0.036	0.037	0.035	0.035	0.036	0.036	0.036	0.036	0.036	0.036
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DIV			-2.301	-1.977	-2.072	-2.117	-2.230	-2.240	-2.262	-2.404	-2.481	-2.575	-2.572	-2.547	-2.547	-2.557	-2.549	-2.549	-2.544	-2.549	-2.549
			0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SAMS				-0.021	-0.018	-0.021	-0.014	-0.013	-0.011	-0.010	-0.027	-0.030	-0.030	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033
				0.002	0.002	0.010	0.069	0.094	0.108	0.166	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CR					-0.034	-0.035	-0.038	-0.038	-0.038	-0.034	-0.033	-0.031	-0.030	-0.029	-0.029	-0.029	-0.028	-0.028	-0.028	-0.028	-0.028
					0.002	0.001	0.000	0.001	0.001	0.012	0.013	0.020	0.020	0.024	0.024	0.024	0.024	0.000	0.024	0.024	0.029
BS						0.230	0.095	-0.110	-0.085	0.177	0.612	0.697	0.692	0.766	0.766	0.767	0.766	0.766	0.765	0.766	0.766
						0.466	0.756	0.715	0.773	0.556	0.031	0.016	0.018	0.012	0.013	0.013	0.013	0.013	0.013	0.013	0.016
D1							0.112	0.098	0.102	0.044	0.035	0.031	0.031	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
							0.000	0.000	0.000	0.000	0.000	0.004	0.005	0.012	0.013	0.012	0.013	0.013	0.013	0.013	0.016
D2								-0.087	-0.079	-0.080	-0.080	-0.079	-0.079	-0.081	-0.081	-0.081	-0.081	-0.081	-0.081	-0.081	-0.081
								0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
D3									0.025	0.009	0.005	0.009	0.010	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.008
									0.156	0.613	0.695	0.438	0.408	0.552	0.552	0.534	0.516	0.516	0.529	0.516	0.529
D4										0.206	0.181	0.172	0.169	0.168	0.168	0.168	0.168	0.168	0.168	0.168	0.168
										0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ATCS (-											-0.509	-0.506	-0.644	-0.557	-0.557	-0.535	-0.183	0.011	-0.242	-0.365	-0.503
1)											0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RIR												0.007	0.012	0.010	0.010	0.009	0.006	-0.587	-	0.007	0.013
												0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000
D (DER)													0.100	0.103	0.103	0.094	0.036	0.218	-	0.095	0.147
													0.004	0.000	0.000	0.003	0.026	0.000	-	0.000	0.000
FBCS														-	-	-	-	-	0.024	-	-
														-	-	-	-	-	0.000	-	-

Table 8: Regression results: panel least squares (all banks) (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
CPI														0.001	0.001	0.001	0.006	0.003	0.010	0.002	-0.001
														0.000	0.028	0.319	0.000	0.000	0.000	0.004	0.207
KSEH															0.000	0.000	0.000	0.000	0.000	0.000	0.000
															0.998	0.824	0.000	0.011	0.000	0.000	0.086
NER																0.000	0.000	-0.006	-0.001	0.000	0.004
																0.635	0.935	0.000	0.320	0.710	0.012
LPTS																		2.858			-
																		0.000			-
Log RGDP																	-2.309	-	-3.916	-	-
																	0.000	-	0.000	-	-
PCI																	-	-	-	-0.000	-
																	-	-	-	0.000	-
D5																					-0.040
																					0.000
Periods	9	9	9	9	9	9	9	9	9	9	8	8	8	8	8	8	8	8	8	8	8
Cross-sections	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
Obs.	339	339	339	339	339	339	339	339	339	339	300	300	300	300	300	300	300	300	300	300	300
R^2	0.2800	0.3919	0.4750	0.4962	0.5102	0.5109	0.5537	0.5715	0.5726	0.6110	0.6424	0.6521	0.6543	0.6567	0.6567	0.6567	0.6573	0.6573	0.6572	0.6573	0.6573
Adj. R^2	0.2779	0.3883	0.4703	0.4901	0.5029	0.5021	0.5443	0.5611	0.5609	0.5992	0.6287	0.6376	0.6386	0.6398	0.6386	0.6373	0.6366	0.6366	0.6379	0.6366	0.6366

Note: The upper row for each variable reports the sign and magnitude of the coefficient, while the lower row gives the p-value. Where the coefficient is 0, this is due to rounding to three decimal places.
Source: Author's calculations.

Table 9: Regression results: panel least squares (excluding specialized banks)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
C	0.1565	0.1178	0.0871	0.0603	0.0200	-0.1112	-0.0852	0.0406	0.0643	0.5054	0.5005	0.5774	0.4926	9.0273	0.3744
	0.0000	0.0002	0.0063	0.3593	0.7636	0.2329	0.3230	0.5744	0.4211	0.0000	0.0000	0.0000	0.0000	0.6667	0.9861
CG	0.0001	0.0001	0.0006	0.0006	0.0006	0.0006	0.0004	0.0006	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
	0.7835	0.6597	0.0335	0.0305	0.0268	0.0002	0.0026	0.0003	0.0051	0.0298	0.0292	0.0351	0.0354	0.0415	0.0303
LIR		0.1879	0.3546	0.3612	0.3564	0.3960	0.3258	0.4511	0.4476	0.3457	0.3434	0.3193	0.3189	0.3181	0.4716
		0.1854	0.0032	0.0013	0.0014	0.0000	0.0000	0.0000	0.0000	0.0006	0.0008	0.0026	0.0026	0.0032	0.0020
DIV			-3.2583	-3.2892	-3.2711	-2.8896	-2.8642	-2.6472	-2.7127	-2.8102	-2.8189	-2.8391	-2.8391	-2.8436	-2.9102
			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SAMS				0.0017	0.0047	0.0113	0.0117	0.0024	0.0011	-0.0007	-0.0011	-0.0010	-0.0011	-0.0011	-0.0105
				0.7138	0.3608	0.1366	0.1055	0.6919	0.8658	0.9050	0.8465	0.8609	0.8535	0.8579	0.1448
CR				-0.0037	0.0007	-0.0236	-0.0223	-0.0129	-0.0105	-0.0054	-0.0049	-0.0050	-0.0051	-0.0052	-0.0065
				0.6860	0.9456	0.0249	0.0231	0.0763	0.1202	0.5199	0.5718	0.5607	0.5571	0.5412	0.4945
BS					-0.1488	-0.3562	-0.5251	-0.4852	-0.4418	-0.3981	-0.3869	-0.3884	-0.3871	-0.3870	-0.0953
					0.4457	0.1560	0.0341	0.0194	0.0249	0.0280	0.0363	0.0347	0.0352	0.0351	0.5410
D1						0.1409	0.1276	0.1118	0.1105	0.1086	0.1082	0.1082	0.1082	0.1082	0.0937
						0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D2							-0.0691	-0.0828	-0.0839	-0.0873	-0.0876	-0.0880	-0.0881	-0.0880	-0.0929
							0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D3								-0.0767	-0.0766	-0.0708	-0.0711	-0.0688	-0.0688	-0.0686	-0.0654
								0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D5									-0.0320	-0.0115	-0.0119	-0.0149	-0.0256	-0.0358	-0.0354
									0.0025	0.0022	0.0033	0.0016	0.0002	0.1612	0.0748
ATCS (-1)										-0.3601	-0.3499	-0.4204	-0.3658	-0.2504	-0.2782
										0.0000	0.0000	0.0000	0.0000	0.2746	0.1526
RIR											0.0005	0.0030	0.0028	0.0084	0.0049
											0.5351	0.0297	0.0458	0.5769	0.7444
D(DER)												0.0544	0.0437	0.0348	0.0436
												0.0031	0.0261	0.0000	0.0000
FBCS													0.0085	0.0002	0.0169
													0.0056	0.9933	0.5161

Table 9: Regression results: panel least squares (excluding specialized banks) (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Log RGDP														-0.2890	0.0011
														0.6836	0.9987
D6															0.0900
															0.0000
Periods	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7
Cross-sections	38	38	38	38	38	38	38	38	38	38	38	38	38	38	38
Observations	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246
R^2	0.0091	0.2114	0.2120	0.2120	0.2129	0.3671	0.3916	0.4036	0.4100	0.4250	0.4740	0.4757	0.4758	0.4757	0.5479
Adjusted R^2	0.0009	0.2017	0.1989	0.1956	0.1931	0.3485	0.3710	0.3809	0.3849	0.3980	0.4469	0.4463	0.4440	0.4416	0.5133

Note: The upper row for each variable reports the sign and magnitude of the coefficient, while the lower row gives the p-value.
Source: Author's calculations.

Table 10: Regression results: FE model

	1	2	3	4	5	6	7
C	0.1007	0.1106	0.1241	0.1253	0.1697	0.2376	0.8007
	0.0001	0.1729	0.1105	0.1173	0.0086	0.0014	0.0067
NPLGA (-1)	0.4536	0.4516	0.3915	0.3527	0.3488	0.3345	0.3158
	0.0043	0.0054	0.0191	0.0333	0.0339	0.0407	0.0460
CCM		-0.0185	-0.0396	-0.0306	-0.1119	-0.1179	-0.0591
		0.8883	0.7606	0.8168	0.2621	0.2443	0.6275
LIR			0.0192	0.0235	0.0221	0.0220	0.0194
			0.0525	0.0012	0.0043	0.0041	0.0055
DIV				-1.6211	-1.6576	-1.6256	-1.6316
				0.0000	0.0000	0.0000	0.0000
CR					-0.0512	-0.0503	-0.0408
					0.0026	0.0019	0.0100
BS						-2.3295	-0.6726
						0.0001	0.5098
SAMS							-0.0430
							0.0697
Periods	8	8	8	8	8	8	8
Cross-sections	40	40	40	40	40	40	40
Observations	299	299	299	299	299	299	299
R^2	0.7750	0.7750	0.7873	0.8026	0.8061	0.8085	0.8187
Adj. R^2	0.7328	0.7318	0.7454	0.7628	0.7661	0.7680	0.7795

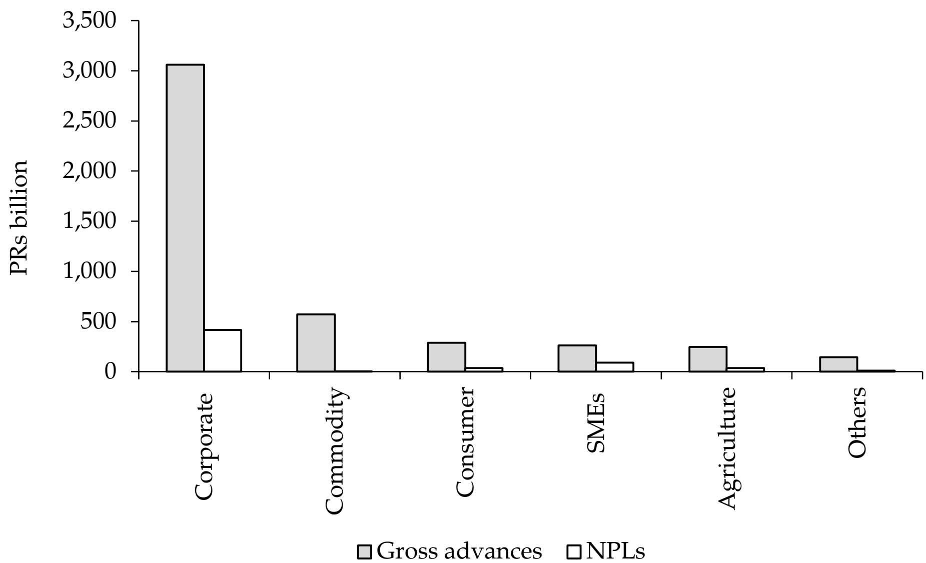
Note: The upper row for each variable reports the sign and magnitude of the coefficient, while the lower row gives the p-value.
Source: Author's calculations.

The positive and significant coefficient (at a 5 percent confidence level) of the public ownership dummy across all specifications corroborates the common perception. It is interesting to note that NPLs are significantly (at a 1 percent confidence level) and negatively associated with the dummy for Islamic banks. The coefficient of the foreign bank dummy is insignificant at conventional levels, and that of the dummy for specialized banks is positive and significant (at a 1 percent confidence level).

The negative and significant coefficient (at a 1 percent confidence level) of asset utilization signifies that a decline in asset turnover damages the ability of the corporate sector to repay its debts, thus raising the NPL level. This implies that the utilization of corporate assets is far more important than merely expanding the asset base through debt financing to repay bank loans.

Consistent with the findings of Hussain (2012), the study's results suggest that the RIR has a positive and significant impact (at a 5 percent confidence level) on NPLs across all specifications. The financial burden and DER of the corporate sector also have a significant (at 1 percent) and positive effect on NPLs. Larger loans indicate a higher DER, which raises the magnitude of NPLs. It also implies that larger loans are more likely to become NPLs and vice versa – a finding that reflects the data presented in Figure 7, where those sectors that account for the largest shares of bank lending also have higher NPLs (with the exception of commodities).

Figure 7: Gross advances and NPLs, by sector



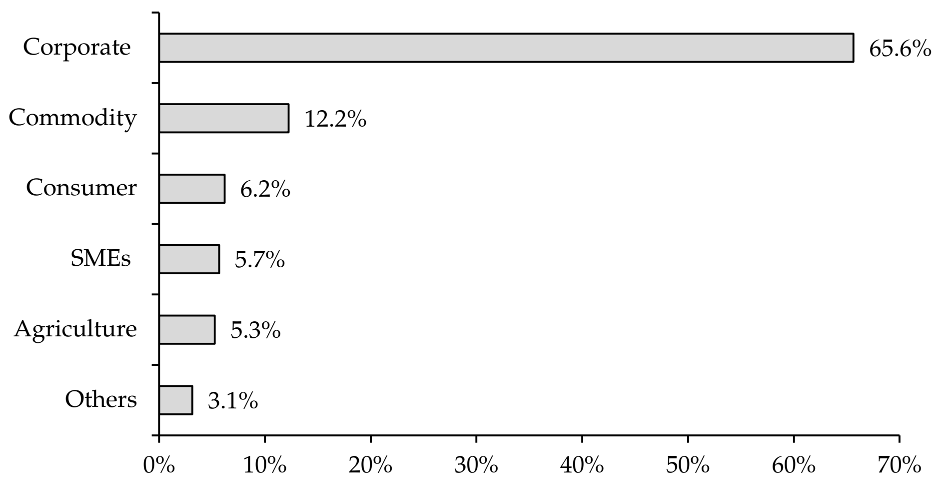
Source: Author's calculations based on data from the State Bank of Pakistan.

Consistent with the findings of Klein (2013), a higher cost of living affects the ability of borrowers to repay their loans: the variable has a positive, significant (at 5 percent) and stable coefficient across all specifications. Although stock price movements have a positive, if very small impact on NPLs (coefficient = 0.0000031), the statistical significance of the coefficient is not robust across all specifications – this finding contradicts Beck et al. (2015). While there is insufficient data to generate evidence, one might expect upward stock price movements to lead to higher expected stock prices, which could motivate investors to borrow further and divert their cash flows toward investment in stocks instead of loan repayment, especially where loan terms are poorly enforced.

The impact of movements in the exchange rate is insignificant. An adverse macroeconomic environment (a lower real GDP growth rate) raises NPLs and vice versa. This finding is consistent with Klein (2013), Messai and Jouini (2013), Beck et al. (2015) and Anastasiou et al. (2016). It is worth noting that the share of bank lending channeled to the textiles sector (and the fact that this share has increased) has a significant and positive impact on NPLs. This can be interpreted as a positive association between political connectedness or influence and NPLs.

With a few exceptions, the study's results remain largely the same when we exclude specialized banks with an NPL rate of 100 percent. Credit growth, whether measured as a proportion of gross advances or of total assets, or simply as the growth of gross advances, has a positive and significant effect on NPLs regardless of whether the sample includes specialized banks (Tables 8 and 9). This also holds for the impact of bank diversification, bank ownership, corporate asset turnover, corporate financial leverage (the DER) and the global financial crisis. Figure 8 illustrates the significant and positive impact of the share of bank lending to the corporate sector on the NPL rate (see also Table 9).

Figure 8: Credit share, by sector



Source: Author's calculations based on data from the State Bank of Pakistan.

The results of the FE model show that the coefficients of bank diversification, the capitalization ratio, bank size and the scale of loan appraisal and monitoring are negative and significant, while the feedback effect of previous NPLs and the lending interest rate are significant and positive. However, the impact of credit growth on NPLs is insignificant. The sign and significance of most of the bank-specific variables are robust across the two models, with the exception of bank size and credit growth.

7. Conclusion and Policy Implications

The regression results suggest that credit market concentration or credit growth, the lending rate, the cost of living, the bank's market power (bank size), public sector ownership, specialized banking, the DER and financial burden have a positive and significant impact on NPLs. The diversification of bank activities, the scale of loan appraisal and monitoring, Islamic banking, corporate asset turnover and a favorable macroeconomic environment significantly reduce the NPL rate. Stock price movements have a very small positive (0.0000031) effect that is significant across some, but not all, specifications. The impact of foreign banking and nominal exchange rate movements is insignificant because bank lending to foreign borrowers is negligible.

An important finding is that bank-specific indicators have greater explanatory power with respect to the variation in NPLs than corporate sector indicators. Macroeconomic indicators have the least (almost negligible) explanatory power: their addition to the model has little or no impact on the R^2 term. Moreover, the results for the key variables remain similar regardless of whether we include or exclude specialized banks with a 100 percent NPL rate. Finally, the relatively large share of bank lending to the corporate sector clearly increases NPLs.

The study's findings have several policy implications:

- If regulators and policy advisors are to manage the NPL rate better, they need to take into account the relevant corporate sector indicators – in addition to bank-specific and macroeconomic variables – when assessing the vulnerable points of the banking and financial sectors.
- The State Bank of Pakistan should focus on strengthening loan appraisal and monitoring systems, especially in conventional and specialized banking. It also needs to ensure that bank credit penetrates segments other than the corporate sector. This entails limiting the pace of credit growth and loan size in the corporate sector's case, given that (i) its financial burden and DER have a positive effect on NPLs and (ii) larger loans are more likely to become NPLs. Giving banks incentive to diversify their activities could also help reduce the NPL rate.

- The Competition Commission of Pakistan should take measures to reduce the market power of larger banks by promoting competition in the sector.
- Finally, corporate managers need to diversify bank activities and monitor their asset turnover, capital structure and financial burden in addition to other indicators, especially when lending to corporate entities.

References

Adhikary, B. K. (2006). Nonperforming loans in the banking sector of Bangladesh: Realities and challenges. *Ritsumeikan Journal of Asia Pacific Studies*, *21*, 75–95.

Anastasiou, D., Lourie, H., & Tsionas, M. (2016). Determinants of nonperforming loans: Evidence from Euro-area countries. *Finance Research Letters*, *18*, 116–119.

Beck, R., Jakubik, P., & Piloiu, A. (2015). Key determinants of nonperforming loans: New evidence from a global sample. *Open Economies Review*, *26*(3), 525–550.

Beck, T., Demirgüç-Kunt, A., & Merrouche, O. (2013). Islamic vs. conventional banking: Business model, efficiency and stability. *Journal of Banking and Finance*, *37*(2), 433–447.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking and Finance*, *21*(6), 849–870.

Berger, A. N., & Udell, G. F. (2004). The institutional memory hypothesis and the pro-cyclicality of bank lending behavior. *Journal of Financial Intermediation*, *13*(4), 458–495.

Bernanke, B. S., & Lown, C. S. (1991). The credit crunch. *Brookings Papers on Economic Activity*, *2*, 205–247.

Boudriga, A., Taktak, N. B., & Jellouli, S. (2010). *Bank-specific, business and institutional environment determinants of banks' nonperforming loans: Evidence from MENA countries* (Working Paper No. 547). Giza, Egypt: Economic Research Forum.

Çifter, A. (2015). Bank concentration and nonperforming loans in Central and Eastern European countries. *Journal of Business Economics and Management*, *16*(1), 117–137.

De Bock, R., & Demyanets, A. (2012). *Bank asset quality in emerging markets: Determinants and spillovers* (Working Paper No. 71). Washington, DC: International Monetary Fund.

Eisenbeis, R. A. (1997). Bank deposits and credit as sources of systemic risk. *Economic Review* (Federal Reserve Bank of Atlanta), *82*(3), 4–19.

Espinoza, R., & Prasad, A. (2010). *Nonperforming loans in the GCC banking system and their macroeconomic effects* (Working Paper No. 224). Washington, DC: International Monetary Fund.

Fernández de Lis, S., Pagés, J. M., & Saurina, J. (2001). Credit growth, problem loans and credit risk provisioning in Spain. In *Marrying the macro- and micro-prudential dimensions of financial stability* (vol. 1, pp. 331–353). Basel: Bank for International Settlements.

Glen, J., & Mondragón-Vélez, C. (2011). Business cycle effects on commercial bank loan portfolio performance in developing economies. *Review of Development Finance*, *1*(2), 150–165.

Hussain, I. (2012). Growth, corporate gearing and nonperforming loans in Pakistan. *International Journal of Applied Business and Economic Research*, *10*(2), 255–267.

Islam, M. A., Karim, L., & Islam, M. R. (2014). A comparative study of prudential regulation on loan classification and provisioning of the Southeast Asian countries. *Journal of Management Research*, *6*(1), 25–51.

Kauko, K. (2012). External deficits and nonperforming loans in the recent financial crisis. *Economics Letters*, *115*(2), 196–199.

Keeton, W. R. (1999). Does faster loan growth lead to higher loan losses? *Economic Review* (Federal Reserve Bank of Kansas City), *84*(2), 57–75.

Khemraj, T., & Pasha, S. (2009, May). *The determinants of nonperforming loans: An econometric case study of Guyana*. Paper presented at the 3rd Biennial Conference on Business, Banking and Finance, Caribbean Centre for Money and Finance, St Augustine, Trinidad.

Klein, N. (2013). *Nonperforming loans in CESEE: Determinants and impact on macroeconomic performance* (Working Paper No. 72). Washington, DC: International Monetary Fund.

Kwan, S., & Eisenbeis, R. A. (1997). Bank risk, capitalization and operating efficiency. *Journal of Financial Services Research*, *12*(2–3), 117–131.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of nonperforming loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance*, *36*(4), 1012–1027.

Messai, A. S., & Jouini, F. (2013). Micro and macro determinants of nonperforming loans. *International Journal of Economics and Financial Issues*, *3*(4), 852–860.

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, *4*(2), 135–148.

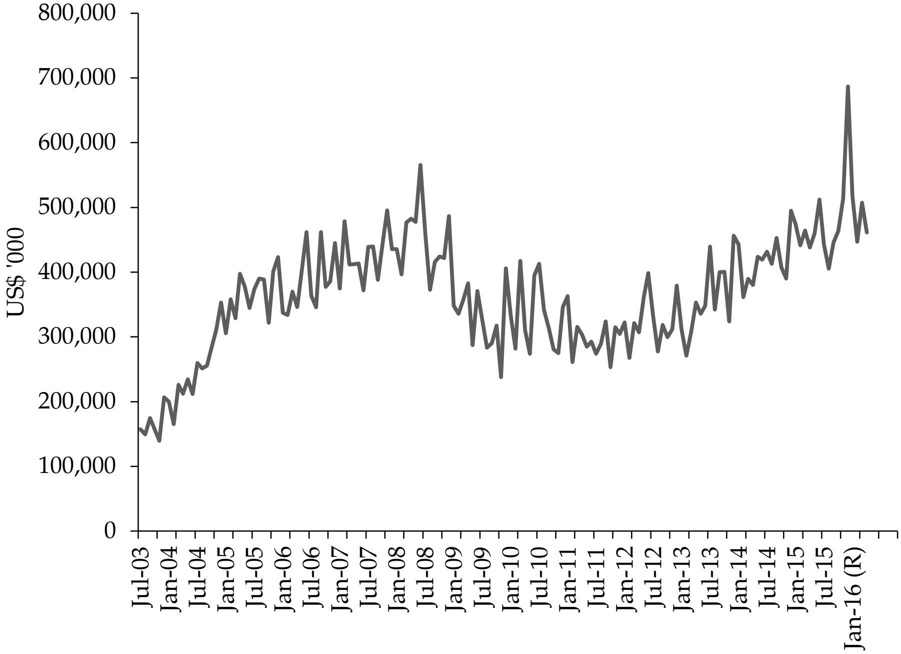
Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*(3), 203–224.

Siddiqui, S., Malik, K. S., & Shah, S. Z. (2012). Impact of interest rate volatility on nonperforming loans in Pakistan. *International Research Journal of Finance and Economics*, *84*, 66–75.

Woo, D. (2000). *Two approaches to resolving nonperforming assets during financial crises* (Working Paper No. 33). Washington, DC: International Monetary Fund.

Appendix

Figure A1: Impact of low or negative RIR regime on imports of machinery and mechanical appliances, 2006–09



Source: Author's calculations based on data from the State Bank of Pakistan.

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Is There a Causal Relationship Between Financial Markets in Asia and the US?

Amalendu Bhunia* and Devrim Yaman**

Abstract

This study examines whether there is a causal relationship between selected stock markets in Asia and the US. Based on stock values from a sample of nine Asian stock markets, we find a positive correlation with US stock market prices in most cases, the exception being Vietnam. Our results indicate significant long-run and short-run causality in both directions between the Asian and US stock markets. These findings show that, while both sets of markets are integrated, there are still valuable opportunities for international investors to diversify their portfolios in the US and Asia.

Keywords: stock market, short and long term causality, Asia, USA.

JEL classification: F21.

1. Introduction

The integration of international capital markets is widely debated in the finance literature. Capital market integration has implications for both policymakers and investors. An important reason for studying this integration concerns the potential gains from international portfolio diversification. The interrelationships among international stock markets have implications for asset allocation as well as risk management. The recent global financial crises and their contagion effects show that co-movements and causal relationships between stock markets need closer analysis.

Asian markets provide valuable opportunities for investors, given that the rise of the middle class in this region has allowed consumption levels to expand, creating numerous pockets of growth. For example, a report by Aberdeen Asset Management, Henderson Global Investors and What Investment (2016) shows that, although economic growth in China has slowed down, its GDP growth rate has remained strong. Moreover,

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the country is characterized by robust domestic consumption, low valuations and reforms in the state-owned enterprise sector. Japan, which has undergone economic reforms to enhance its global competitiveness, has an aging population with large disposable incomes, thereby opening up opportunities for investment in nursing homes, medical equipment and holiday resorts. India continues to attract investors, given the optimism surrounding its economic prospects and stock valuations. Part of this relates to declining commodity and oil prices as the country is a net importer of both. Finally, Korea has experienced positive change with the growing involvement of minority shareholders, who are now taking on a proactive role in their companies and even voting against the board.

The US has long provided foreign investors with attractive opportunities. Not only do they benefit from the country's efficient, liquid and highly developed markets and its strong corporate institutions, but they can also diversify risk when investing in the US, particularly if their own financial markets have a low correlation with the US market (Forbes, 2008).

Deregulation and the liberalization of capital markets, combined with technological advances, have allowed Asian and US markets to become more integrated over time. Numerous financial events point to this increasing correlation. For example, in the summer of 1997, when a large portion of East Asian currencies fell by as much as 38 percent, leading to a sharp drop in the stock market indices of these countries, the Dow Jones Industrial Average (DIJA) plunged by 7.2 percent on 27 October. In early 2016, when Japan cut its short-term interest rates, the US market responded with a drop of 11.5 percent between 1 January and 11 February.

This study investigates the causal relationship between the US financial market and nine Asian markets, including India, China, Japan, the Republic of Korea, Vietnam, Indonesia, Malaysia, the Philippines and Singapore. We test the correlation between these stock markets and the US market to determine the diversification benefits investors might derive. We also study the direction of causality in the long run and short run.

The paper is organized as follows. Section 2 reviews the literature on causal relationships between international financial markets. Section 3 describes the data, methodology and hypotheses employed. Section 4 presents the study's results and Section 5 summarizes our conclusions.

2. Literature Review

The literature on the causal relationship between different stock markets looks at groups of countries at a global or regional level or at a single country relative to other countries. Dheeriya (1993), for example, uses Geweke's (1982) causality test to study the interdependence of 17 stock market indices. The study finds that the UK and US markets have the most influence over other markets relative to key markets such as Japan, France and Canada. Most markets, however, react to movements – past or present – in other markets. Examining the periods before and after the 1987 crash, Dheeriya finds a structural shift in the interrelationship between international stock markets.

Richards (1995) examines long-term returns to establish the degree of cointegration among different markets. Using a simulation method, he finds that the strong cointegrated relationship observed in earlier studies is the result of "a failure to adjust asymptotic critical values to take account of the small degrees of freedom that remain" when using the Johansen multivariate estimation method. The alternative cointegration tests he presents confirm that the null hypothesis of no cointegration is generally not rejected. Based on a sample of 16 stock markets, the study concludes that stock market indices have a common world component as well as a permanent and transitory country-specific component.

Meriç et al. (2012) determine the linkages among international stock markets following the 2008 market crash. The study's Granger causality results show that the US stock market has considerable influence over other stock markets in Europe and Asia. Using principal component analysis to group stock markets by their co-movements, the authors show that global investors can use high factor loadings in different principal components to maximize portfolio diversification. Their time-varying correlation analysis shows that the benefits of international diversification have decreased since 2008, given the growing correlation among international stock markets.

At the regional level, Huang, Yang and Hu (2000) examine cointegration and causality among stock markets in the US, Japan and the South China Growth Triangle.[1] Using advanced unit root and cointegration techniques that allow for structural breaks, they find no

[1] Huang et al., who define this area as Hong Kong, Taiwan and the southern part of the People's Republic of China, argue that a common culture (Confucianism) and language should help create an integrated capital market.

evidence of cointegration among these stock markets, except for the Shenzhen and Shanghai indices. The study shows that price changes in the US can be used to predict next-day price changes in Taiwan and Hong Kong. The returns earned on the Hong Kong and US stock markets are contemporaneous and there is significant feedback between the Shenzhen and Shanghai stock exchanges.

Tabak and Lima (2003) assess cointegration and causality among the US market and a sample of Latin and Central American stock markets (Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela). They find evidence of short-term causality, but none of cointegration. The results establish Granger causality between the Brazilian stock market and the other Latin American stock markets. Using impulse response functions, the authors find that the DIJA has a heterogeneous effect on the other stock markets. The US stock market has the greatest influence over the Mexican stock market, given that the two are highly integrated.

Beine, Capelle-Blancard and Raymond (2008) study the linear and nonlinear relationships among stock markets in the US and four other countries: France, Germany, Japan and the UK. They establish a directional linear dependence from the US to the rest of the sample and a strong contemporaneous linear dependence among the latter. The study shows that, consistent with the financial liberalization of the 1980s and 1990s, causality increased after 1987. The results indicate bidirectional nonlinear causality among the daily returns of these stock markets. The authors filter out heteroskedasticity using a FIGARCH model to test for spurious causality. There is a large fall in the number of significant nonlinear causality lags, which points to heteroskedasticity in previous findings. When structural breaks are controlled for, the linear causality remains, while numerous nonlinear relationships disappear.

Among studies that look at the effect of various stock markets on a single stock market, Panda and Acharya (2011) study the integration of the Indian stock market with the US stock market and key Asian stock markets between 2001 and 2008 – a period during which the Indian stock market was affected by foreign institutional investors continuously moving funds across global markets. Employing Granger causality, vector autoregression (VAR), Johansen–Juselius cointegration and innovation accounting analysis, the study looks at the long-term and short-term dynamic relationships among the sample. It finds that the Indian stock market has a cointegrated relationship with the US stock market. A similar relationship emerges with Hong Kong pre-crisis and with China post-crisis, but there is no significant relationship with the other Asian countries.

Hatemi (2012) analyzes the cointegration between the UAE and US stock markets using symmetric and asymmetric Granger causality. The standard symmetric causality tests show that the UAE market is segmented from the US market. However, the asymmetric causality tests, which separate the causal impact of negative shocks from positive ones, reveal that the UAE market is integrated with the US stock market. The study also finds that the degree of integration is higher when stock markets are falling rather than rising.

Dasgupta (2014) studies the integration of the BRIC stock markets (Brazil, Russia, India and China), using Johansen–Juselius and Engle–Granger cointegration as well as pairwise cointegration tests. The study uses VAR and variance decomposition for a more robust analysis. Its results indicate long-run and short-run bidirectional Granger causality between the Indian and Brazilian stock markets. In addition, movements in the Chinese stock market affect the Brazilian stock market, which in turn affects the Russian stock market. Dasgupta concludes that the BRIC countries are favorable environments for investment and that the Indian stock market tends to dominate its BRIC counterparts.

Rehman and Hazazi (2014) focus on the Saudi stock market and its relationship with stock markets in the Gulf Cooperation Council countries, Japan, the UK and the US. Using Pearson correlation, the unit root test, Johansen cointegration and pairwise causality tests, the study points to growing correlation among these markets over time and a fall in the volatility of the Saudi index (TASI), although there is no evidence that any one stock market drives the others.

Overall, the literature shows that causal relationships exist among international markets, irrespective of geographical proximity. Movements in certain stock markets clearly affect others, but this does not preclude opportunities for diversification internationally. Drawing on this, we assess the causal relationships and potential for diversification in a sample of nine stock markets in Asia with respect to the US stock market.

3. Data and Methodology

The daily time-series data for the nine Asian stock markets and the US stock market was obtained from the Bloomberg, Investing.com and Yahoo Finance databases.[2] The study's sample period is 2 January

[2] Available from https://www.bloomberg.com/asia, https://www.investing.com/ and https://finance.yahoo.com/, respectively. We have selected a combination of developed and developing Asian markets to ensure that the sample is representative of the region.

1991 to 31 March 2016 for all selected stock markets, barring the Hanoi Stock Exchange, which did not become operational until 18 May 2005. In this case, we use the period 18 May 2005 to 31 March 2016.

Given the nature of the analysis, the data is prone to heteroskedasticity. One method of controlling for this is to weight each observation by the inverse of the standard deviation of the error. This is an effective method in a least squares regression analysis once we identify the existence and scale of heteroskedasticity. If it comprises a small number of unidentified parameters, we can measure the variance of every residual and apply the weights to correct the heteroskedasticity. However, if the nature of the heteroskedasticity cannot be determined, an alternative is to use heteroskedasticity-consistent covariance matrices. In nonlinear models, where the nature of heteroskedasticity may be hard to identify, we cannot establish an appropriate variance-stabilizing transformation and assess weights in a least squares analysis (see Long & Ervin, 2000; Greene, 1997). Since the time-series data is skewed and the variances are not constant, we convert the daily time-series data for the ten stock price indices into natural logarithm form to resolve the heteroskedasticity problem (Bhunia, 2012). The sample indices and their corresponding variables are listed below.

Country	**Index name**	**Variable**
India	BSE Sensex	*lsx*
China	Shanghai Stock Exchange (SSE) Composite Index	*lsci*
Japan	Nikkei	*lnk*
Korea	Korea Composite Stock Price Index (KOSPI)	*lkpi*
Vietnam	Hanoi Stock Exchange Equity Index (HNX Index)	*lhnx*
Indonesia	Jakarta Stock Exchange Composite Index (JCI)	*ljci*
Malaysia	FBM Kuala Lumpur Composite Index (KLCI)	*lkci*
Philippines	Philippine Stock Exchange Composite Index (PSEi)	*lpci*
Singapore	FTSE Straits Times Index (STI)	*lsti*
US	Dow Jones Industrial Average (DJIA)	*ldji*

4. Empirical Results and Analysis

This section provides the descriptive statistics for the sample and carries out a correlation analysis, unit root test and Johansen cointegration analysis. It also generates a vector error correction model (VECM) and carries out robustness checks.

4.1. Descriptive Statistics

We start by testing the distribution of the sample. Our null hypothesis is that the stock price indices are distributed normally. This is consistent with Fama (1965) and Aparicio and Estrada (1997) who argue that stock market prices are distributed normally if the indices follow the random walk theory.

Table 1 shows that the Japanese stock market has the highest average (natural logarithm) price (9.57) of the ten stock markets, while the Indonesian stock market has the lowest (3.90), consistent with Lingaraja, Selvam and Vasanth (2015). The median prices follow a similar pattern to the average prices. The Indonesian stock market has the highest average daily stock returns (0.036 percent), while the Thai stock market has the lowest average daily returns (–0.034 percent; not tabulated).

The Indian stock market has the highest standard deviation (0.84) followed by the Chinese stock market (0.71), which indicates that prices in the former are more variable than those in the other stock markets. The kurtosis is greater than the skewness (for which seven out of ten results are negative) across the entire sample, which shows that the distribution is platykurtic. The Jarque–Bera statistics also confirm that the series is not normally distributed. Therefore, the null hypothesis is rejected statistically, which means that the stock prices indices in this sample do not represent a normal distribution.

Table 1: Descriptive statistics

	ldji	**lhnx**	**ljci**	**lkci**	**lkpi**	**lnk**	**lpci**	**lsci**	**lsti**	**lsx**
Mean	9.06	4.72	3.90	6.95	6.89	9.57	7.81	7.28	7.69	8.85
Median	9.24	4.52	3.92	6.93	6.82	9.64	7.78	7.36	7.68	8.55
Max.	9.81	6.13	4.84	7.54	7.71	10.21	9.00	8.71	8.26	10.30
Min.	7.81	3.93	2.16	5.57	5.63	8.86	6.37	4.66	6.69	6.86
SD	0.51	0.53	0.41	0.35	0.56	0.30	0.57	0.71	0.31	0.84
Skewness	-0.82	0.71	-0.47	-0.27	-0.21	-0.25	0.32	-1.18	-0.28	0.14
Kurtosis	2.57	2.52	3.44	2.77	1.96	1.95	2.29	5.19	2.29	1.69
JB stat.	748.6	243.8	282.1	85.2	324.7	350.1	232.4	2,794.5	218.9	455.7
Obs.	6,280	2,582	6,361	6,023	6,221	6,221	6,208	6,440	6,346	6,067

Note: Sample indices denoted by: lsx = Sensex, lsci = SSE Composite Index, lnk = Nikkei, lkpi = KOSPI, lhnx = HNX Index, ljci = JCI, lkci = KLCI, lpci = PSEi, lsti = STI, ldji = DJIA. JB = Jarque–Bera test, SD = standard deviation.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

Secondary stochastic theory is a different justification for the fat tail of the observed allocation of stock price indices. This hypothesis holds that stock price indices are sampled from a range of allotments with diverse, restricted variances. The heteroskedasticity linked with this combination of normal distributions will lead to large kurtosis values in the sample. Consequently, the distribution of fundamental factors is nonstationary over time (see Herve, Chanmalai & Shen, 2011).

4.2. Correlation Analysis

The efficient markets hypothesis is linked to the random walk model, which suggests that, if the information flow is unrestricted, then any new information should be reflected instantly in the stock prices. Since there are numerous common economic factors that affect international stock prices to the extent that these markets are efficient and follow a random walk model, the prices of the sample stock indices should be highly correlated (see Malkiel, 2003). Thus, we hypothesize that the Asian stock markets are positively correlated with the US stock market.

Table 2 gives the correlation coefficients of the stock index prices in our sample. The table shows that the US stock market is negatively correlated with the Vietnamese stock market, but positively correlated with all the other Asian stock markets over the sample period. Interestingly, the Vietnamese stock market is negatively associated with the Indian, Philippine, Korean and Malaysian stock markets as well. These correlation coefficients are statistically significant at the 5 percent level. There is no correlation between the Vietnamese and Singapore stock markets. Four stock markets – the Korean, Malaysian, Singapore and Indian stock markets – show evidence of significant co-movements with the US stock market over the study period. These findings support the hypothesis that the US and Asian markets are highly integrated with each other.

Table 2: Correlation analysis of stock index prices

	ldji	lhnx	ljci	lkci	lkpi	lnk	lpci	lsci	lsti	lsx
ldji	1.00									
lhnx	-0.34	1.00								
ljci	0.44	0.34	1.00							
lkci	0.80*	-0.53*	0.01	1.00						
lkpi	0.72*	-0.44*	0.04	0.92*	1.00					
lnk	0.67	0.25	0.72*	0.19	0.15	1.00				
lpci	0.87*	-0.61*	0.03	0.95*	0.83*	0.30	1.00			
lsci	0.21	0.33	-0.11	0.33	0.43	0.17	0.25	1.00		
lsti	0.68*	0.00	0.50	0.68	0.71	0.39	0.58	0.39	1.00	
lsx	0.78*	-0.39*	-0.01*	0.91*	0.85*	0.31	0.89*	0.47	0.60	1.00

Note: Sample indices denoted by: lsx = Sensex, lsci = SSE Composite Index, lnk = Nikkei, lkpi = KOSPI, lhnx = HNX Index, ljci = JCI, lkci = KLCI, lpci = PSEi, lsti = STI, ldji = DJIA.
* Significant at 5 percent level.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

We use a pairwise correlation analysis to test the linear statistical interdependence between the US and Asian stock markets, but this does not confirm the existence of any stable long-run association. Instead, we use cointegration analysis to demonstrate this association, which gauges the correlation between two nonstationary variables in a stationary way.

4.3. *Unit Root Test Analysis*

A regression analysis using time-series data requires stationary data to produce meaningful results. In the case of nonstationary data, the Johansen cointegration test is used to determine the relationship between variables. A condition for cointegration among the sample stock markets is that their data should be nonstationary and integrated of an order higher than 0. We test stationarity using the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests before proceeding to the cointegration test.

Both the unit root and cointegration tests for pertinent financial indicators help establish time-series attributes. These tests are significant because they demonstrate the number of times a variable must be differenced to yield a stationary value. Financial indicators that are stationary are described as I(0), while those that need to be first-differenced are termed I(1). The ADF and PP tests determine the existence of a unit root. We test the null hypothesis that all the selected stock markets have a unit root against the alternative hypothesis of no unit root.

Table 3 gives the results of the unit root tests, indicating that none of the stock index prices in the sample are originally stationary, but that all of them become stationary when first-differenced. Thus, the null hypothesis is accepted because the stock price indices are not stationary at level. Since the time-series data is nonstationary at level, regular regression would generate spurious results. Accordingly, we use the Johansen cointegration test to determine the existence of long-run associations in the sample.

Table 3: Unit root test results

	At level		First-differenced	
Variable	**ADF t-stat**	**PP t-stat**	**ADF t-stat**	**PP t-stat**
ldji	0.64	0.40	-14.95	-84.03
lhnx	-1.38	-1.42	-18.70	-44.54
ljci	-2.35	-2.32	-57.60	-79.44
lkci	-2.02	-1.92	-11.62	-74.35
lkpi	-1.71	-1.63	-12.87	-73.06
lnk	-1.50	-1.54	-58.37	-81.83
lpci	-0.86	-0.72	-19.07	-66.47
lsci	0.04	0.30	-14.42	-77.52
lsti	-1.46	-1.29	-20.01	-73.47
lsx	0.03	0.04	-16.73	-70.88

Note: Sample indices denoted by: lsx = Sensex, lsci = SSE Composite Index, lnk = Nikkei, lkpi = KOSPI, lhnx = HNX Index, ljci = JCI, lkci = KLCI, lpci = PSEi, lsti = STI, ldji = DJIA.
* Significant at 5 percent level. Coefficient of variation at 5 percent is –2.86, indicating that the decision is not stationary at level and stationary when first-differenced.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

4.4. Johansen Cointegration Analysis

Financial theory holds that economic variables should be integrated or follow a random walk. Cointegration tests help identify any significant association between variables. Variables with diverse trends cannot have a long-run association with each other, suggesting that there is generally no support for deductions based on model allocations (Sjö, 2008). In general, we presume that the system is integrated of order I(1), the idea being that international stock markets are likely to be cointegrated under the Johansen cointegration test assumption (Yusupov & Duan, 2010) since many of the same variables affect market performance, resulting in cointegration in the long run.

Before performing the test, we need to determine the optimal lag length for the sample. This applies to the Johansen cointegration test as well as the vector error correction and causality tests. The criteria used here are the Akaike information criterion (AIC), the Schwarz Bayesian criterion (SBC) and the Hannan–Quinn criterion (HQC). Keeping in mind that a smaller lag length implies a better model, we choose a maximum lag order of 2. Table A1 in the Appendix shows that the SBC and HQC yield a lag order of 1 and the AIC a lag order of 2. Ivanov and Kilian (2001) argue that the SBC and HQC provide better results for quarterly models, whereas the AIC should be used in models spanning a shorter period. Since we are using daily data, we select an optimal lag length of 2 (the AIC yields a minimum value of –55.34 overall).

Johansen cointegration is a standard method of determining long-run relationships in time-series data in a VECM. Having established that the prices of the stock market indices in our sample become stationary when first-differenced and selected a lag length of 2, we use a critical value of 5 percent in the Johansen cointegration test (Osterwald-Lenum, 1992). Additionally, we employ a complementary deduction procedure involving deterministic factors on the condition that the linear trend is assumed to be fundamentally linear and not quadratic (Lütkepohl & Saikkonen, 2000).

The cointegration test results are given in Table 4, which measures two likelihood ratios: the maximum eigenvalues and trace statistics. The latter exceed their critical value ($r \leq 0$ and $r \leq 4$), with five cointegrating equations. The maximum eigenvalue statistics exceed their critical value ($r \leq 0$ and $r \leq 4$), with five cointegrating equations, which is significant at the 5 percent level. Therefore, both test results confirm the long-run association among the selected variables, consistent with Bhunia (2013) and Hussin et al. (2013). The long-run relationship among the ten stock market indices is illustrated in Figure 1.

Table 4: Johansen cointegration test results

Unrestricted cointegration rank test (trace)

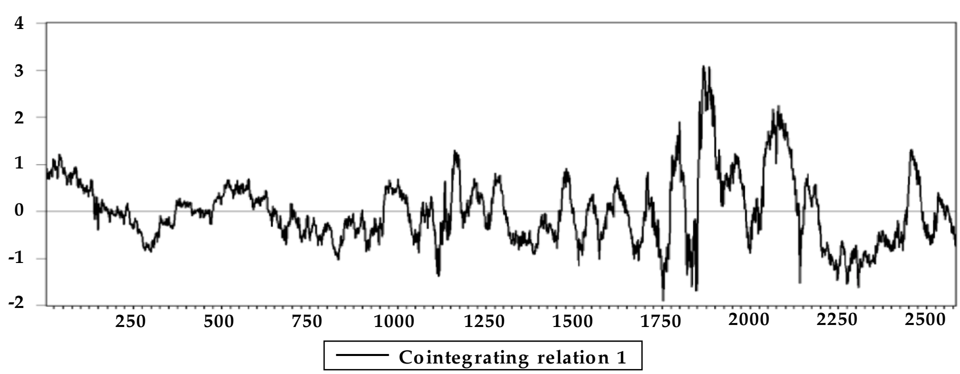
Hypothesized number of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Probability
r ≤ 0*	0.04	461.80	239.23	0.00
r ≤ 1*	0.03	341.23	197.37	0.00
r ≤ 2*	0.02	247.31	159.52	0.00
r ≤ 3*	0.02	173.83	125.61	0.00
r ≤ 4*	0.01	103.87	95.75	0.01
r ≤ 5	0.01	68.92	69.81	0.05
r ≤ 6	0.01	46.46	47.85	0.06
r ≤ 7	0.01	26.24	29.79	0.12
r ≤ 8	0.00	13.24	15.49	0.10
r ≤ 9	0.00	3.49	3.84	0.06

Unrestricted cointegration rank test (maximum eigenvalue)

Hypothesized number of CE(s)	Eigenvalue	Max eigen statistic	0.05 critical value	Probability
r ≤ 0*	0.04	120.57	64.50	0.00
r ≤ 1*	0.03	93.92	58.43	0.00
r ≤ 2*	0.02	73.47	52.36	0.00
r ≤ 3*	0.02	69.95	46.23	0.00
r ≤ 4*	0.01	44.94	40.07	0.01
r ≤ 5	0.01	22.45	33.87	0.57
r ≤ 6	0.01	20.22	27.58	0.32
r ≤ 7	0.01	13.00	21.13	0.45
r ≤ 8	0.00	8.74	14.26	0.30
r ≤ 9	0.00	3.49	3.84	0.06

Note: * Rejection of hypothesis at 5 percent level. Probability = MacKinnon–Haug–Michelis p-values. Max eigenvalue test indicates cointegrating equations at 5 percent level.
Source: Authors’ calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

Figure 1: Cointegration among stock market indices



Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

4.5. *Vector Error Correction Analysis*

Since the stock price indices in the sample have more than one cointegrating vector, we use a VECM that adjusts to short-term transformations in variables as well as divergences from stability. The cointegration rank confirms the number of cointegrating vectors. For example, a rank of 5 indicates that those five linearly independent combinations of nonstationary variables will be stationary. A negative coefficient in the error correction model indicates that any short-run variations between the exogenous and endogenous variables will lead to a steady long-term association among the variables (Asari et al., 2011). Thus, when long-run causality survives, the short-run causality should be tested (Joshi, 2013).

Given that the stock index values are not stationary at level (have to be first-differenced to become stationary) and are cointegrated of the same order, we cannot use an unrestricted VAR model. Thus, we use a restricted VAR model or VECM with an optimal lag length of 2 (see above) and the residuals of the model to test causality (Table 5). To examine the causal relationship between the US stock market and Asian stock markets in the short run and long run, we use the average stock prices of the nine Asian stock markets. The results confirm that there is a long-term relationship between the US and Asian stock markets. The natural logarithm of the price of the DIJA (*ldji*) and the natural logarithm of the average price of the Asian stock markets (*lasma*) are used as dependent as well as independent variables. We estimate the VECM as follows:

$$D(ldji) = -0.01\ (ldji(-1) + 2.25\ lasma(-1) - 25.29) - 0.05\ D(ldji(-1)) - 0.04\ D(ldji(-2)) + 0.01\ D(lasma(-1)) + 0.01 D(lasma(-2)) - 0.0003$$

$$D(lasma) = -0.02\ (ldji(-1) + 2.25\ lasma(-1) - 25.29) - 0.01\ D(ldji(-1)) - 0.01\ D(ldji(-2)) + 0.02\ D(lasma(-1)) - 0.004\ D(lasma(-2)) - 0.0003$$

In Table 5, C(1) and C(7) are the coefficients of the cointegrating model and error correction term, which demonstrates the speed of adjustment toward equilibrium. This variable is the residual of the one-period lag of the cointegrating vector of the US stock market and selected Asian stock markets. Both C(1) and C(7) are negative (–0.01 and –0.02) and statistically significant since the probability is 0. This indicates a significant degree of long-run causality between the US and Asian stock markets. Both the R2 and adjusted R2 terms are more than 0.60, indicating that the data fits the model well. The probability of the F-statistic is 0.00, which implies that the Asian stock market indices (*asma*) have a significant effect on the DIJA (*dji*).

Next, we test the short-run association between the Asian stock markets and the US market by estimating the coefficients of the lagged difference terms and using the Wald test to determine the existence of short-run causality. Table 6 indicates that the probability of the Wald test statistic is lower than 0.05 in both cases, implying that there is significant short-term causality in both directions (to and from the Asian and US stock markets).

Table 5: VECM test results

Error correction	D (ldji)	D (lasma)
CointEq1	-0.01	-0.02
	[0.60]	[3.29]
	(0.00)	(0.00)
D (*ldji* (-1))	-0.05	-0.01
	[-4.57]	[-0.42]
	(0.00)	(0.00)
D (*ldji* (-2))	-0.04	-0.01
	[-3.29]	[-1.02]
	(0.00)	(0.03)
D (*lasma* (-1))	0.01	0.02
	[1.86]	[1.85]
	(0.04)	(0.03)
D (*lasma* (-2))	0.00	-0.00
	[0.40]	[-0.32]
	(0.04)	(0.02)
C	-0.00	-0.00
	[-2.38]	[-1.83]
	(0.01)	(0.05)
R^2	0.61	0.67
Adjusted R^2	0.59	0.63
F-statistic	5.97	4.11
Probability	0.00	0.00

Note: Sample indices denoted by: *lasma* = selected Asian stock market indices, *ldji* = DJIA. t-statistics given in brackets and probabilities in parentheses.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

Table 6: Short-run causality (Wald test) results

Test statistic	Value	df	Probability
	Equation: *ldji* and *lasma*		
Chi-square	21.23	2	0.00
	Equation: *lasma* and *ldji*		
Chi-square	11.07	2	0.00

Note: Sample indices denoted by: *lasma* = selected Asian stock market indices, *ldji* = DJIA.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

4.6. Robustness Checks

For the VECM and Wald model above to fit the data, the following conditions must hold: (i) there should be no serial correlation in the residuals, (ii) the residuals should be homoskedastic and normally distributed, and (iii) the model should be stable. The Breusch–Godfrey LM, Breusch–Pagan–Godfrey and Jarque–Bera tests determine serial correlation, heteroskedasticity and distribution, respectively, and we generate a cumulative sum control chart (CUSUM) to gauge stability. Table 7 and Figure 2 give the results of the residual tests.

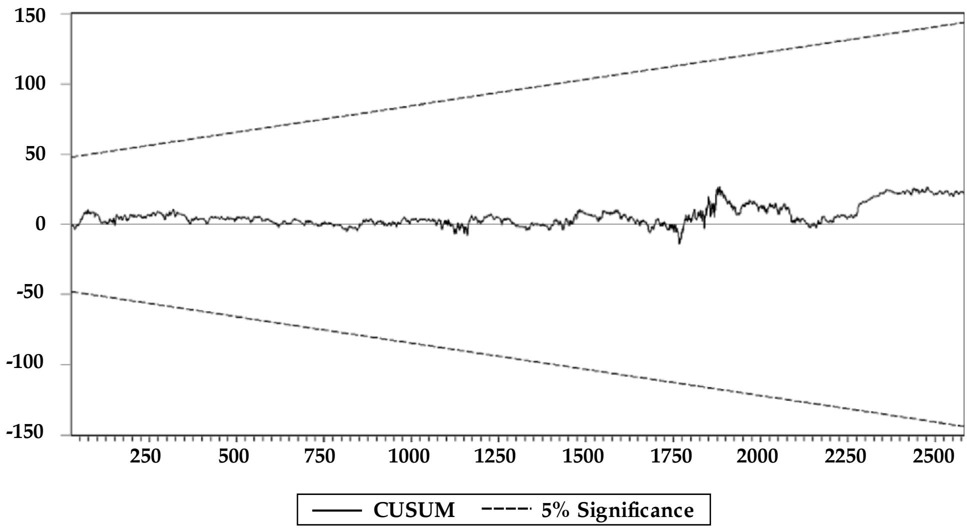
Table 7: Robustness test results

Test	Value	Probability	Value
Serial correlation			
Breusch–Godfrey LM			
F-statistic	2.92	Prob. F (22,556)	0.053
Obs.* R^2	5.89	Prob. chi-square (2)	0.052
Heteroskedasticity			
Breusch–Pagan–Godfrey			
F-statistic	122.43	Prob. F (302,549)	0.056
Obs.* R^2	938.97	Prob. chi-square (30)	0.054
Normality			
Jarque–Bera			
JB statistic	499.23	Probability	0.065

Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

The Breusch–Godfrey serial correlation LM test statistic shows that there is no serial correlation because the probability of the observed R-squared term (0.052) is greater than 0.05. The Breusch–Pagan–Godfrey heteroskedasticity test result indicates the absence of heteroskedasticity as the probability of the observed R-squared term (0.054) is greater than 0.05. The Jarque–Bera statistic is greater than 0.05, which indicates that the residuals are normally distributed. Finally, the CUSUM test results indicate that the model is stable as the data falls within the 5 percent significance level (Figure 2).

Figure 2: CUSUM test results for model stability



Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

5. Conclusion

This study examines the causal relationship between nine Asian stock markets and the US financial market. We find a positive association between the latter and most of the Asian stock markets in our sample. An exception is the Vietnamese stock market, which has a negative correlation with the US financial market, indicating opportunities for diversification by investors.

The time series stock index values are not stationary at level but stationary at first difference. The Johansen cointegration test results indicate that all the stock markets have a long-run association of the same order. The VECM test results confirm that there is significant long-run as well as short-run causality in both directions between the US financial market and the rest of the sample. These findings reflect the degree of integration between the US and Asian stock markets, but also point to valuable opportunities for international investors to diversify their portfolios across these markets.

References

Aberdeen Asset Management, Henderson Global Investors and What Investment. (2016). *Investing in Asia: Turning to the Far East for high returns*. London: Authors. Available from http://asia.investmentintelligence.co.uk/

Aparicio, F., & Estrada, J. (1997). *Empirical distributions of stock returns: Scandinavian securities markets, 1990–95*. Unpublished manuscript, Carlos III University, Madrid.

Asari, F. F. A. H., Baharuddin, N. S., Jusoh, N., … Jusoff, K. (2011). A vector error correction model (VECM) approach in explaining the relationship between interest rate and inflation towards exchange rate volatility in Malaysia. *World Applied Sciences Journal*, *12*, 49–56.

Beine, M., Capelle-Blancard, G., & Raymond, H. (2008). International nonlinear causality between stock markets. *European Journal of Finance*, *14*(8), 663–686.

Bhunia, A. (2012). Association between crude price and stock indices: Empirical evidence from Bombay Stock Exchange. *Journal of Economics and Sustainable Development*, *3*(3), 25–34.

Bhunia, A. (2016, April). *Dependence of Indian stock market on major ASEAN stock markets*. Paper presented at the International Symposium on Business and Management, Bangkok.

Dasgupta, R. (2014). Integration and dynamic linkages of the Indian stock market with BRIC: An empirical study. *Asian Economic and Financial Review*, *4*(6), 715–731.

Dheeriya, P. L. (1993). Further evidence on causality and feedback across international stocks. *Journal of Economics and Finance*, *17*(3), 160–167.

Fama, E. F. (1965). The behavior of stock-market prices. *Journal of Business*, *38*(1), 34–105.

Forbes, K. J. (2008). *Why do foreigners invest in the United States?* (Working Paper No. 13908). Cambridge, MA: National Bureau of Economic Research.

Greene, W. H. (1997). *Econometric analysis* (3rd ed.). Upper Saddle River, NJ: Prentice Hall.

Hatemi, A. (2012). Is the UAE stock market integrated with the USA stock market? New evidence from asymmetric causality testing. *Research in International Business and Finance*, *26*(2), 273–280.

Herve, D. B. G., Chanmalai, B., & Shen, Y. (2011). The study of causal relationship between stock market indices and macroeconomic variables in Cote d'Ivoire: Evidence from error-correction models and Granger causality test. *International Journal of Business and Management*, *6*(12), 146–169.

Huang, B.-N., Yang, C.-W., & Hu, J. W.-S. (2000). Causality and cointegration of stock markets among the United States, Japan and the South China Growth Triangle. *International Review of Financial Analysis*, *9*(3), 281–297.

Hussin, M. Y. M, Muhammad, F., Razak, A. A., Tha, G. P., & Marwan, N. (2013). The link between gold price, oil price and Islamic stock market: Experience from Malaysia. *Journal of Studies in Social Sciences*, *4*(2), 161–182.

Ivanov, V., & Kilian, L. (2001). *A practitioner's guide to lag-order selection for vector autoregressions* (Discussion Paper No. 2685). London: Centre for Economic Policy Research.

Joshi, A. (2013). Long-term causality of GDP-led export (GLE) using VECM model with reference to India. *Prestige International Journal of Management and IT*, *2*(1), 15–25.

Lingaraja, K., Selvam, M., & Vasanth, V. (2015). Long-run dynamic linkages between emerging stock markets in Asia and a developed stock market (DJIA). *Research Journal of Applied Sciences*, *10*(5), 203–211.

Long, J. S., & Ervin, L. H. (2000). Using heteroscedasticity-consistent standard errors in the linear regression model. *American Statistician*, *54*(3), 217–224.

Lütkepohl, H., & Saikkonen, P. (2000). Testing for the cointegrating rank of a VAR process with a time trend. *Journal of Econometrics*, *95*(1), 177–198.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, *17*(1), 59–82.

Meriç, G., Lentz, C., Schmeltz, W., & Meriç, I. (2012). International evidence on market linkages after the 2008 stock market crash. *International Journal of Business and Finance Research*, *6*(4), 45–57.

Osterwald-Lenum, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*, *54*(3), 461–472.

Panda, P. K., & Acharya, D. (2011). Stock market integration: Evidence from India and other major world stock markets. *Indian Journal of Economics and Business*, *10*(4), 605–628.

Rehman, M. Z., & Hazazi, M. A. (2014). Examining linkages between Saudi stock market (TASI) and selected stock market indices. *International Journal of Financial Research*, *5*(4), 196–209.

Richards, A. J. (1995). Co-movements in national stock market returns: Evidence of predictability, but not cointegration. *Journal of Monetary Economics*, *36*(3), 631–654.

Sjö, B. (2008). *Testing for unit roots and cointegration*. Unpublished manuscript, Linköping University, Sweden. Retrieved from https://pdfs.semanticscholar.org/7ce6/2a0c7f6dab85f264a5403bf9b99a0f20a156.pdf

Tabak, B. M., & Lima, E. J. A. (2003). Causality and cointegration in stock markets: The case of Latin America. *Brazilian Journal of Business Economics*, *3*(2), 27–45.

Thorpe, D. (2016). Investing in Asia. Aberdeen Henderson Global Investors Bulletin.

Yusupov, G., & Duan, W. (2010). *Long-run relationships between base metals, gold and oil*. Unpublished Master's thesis, Lund University, School of Economics and Management, Lund, Sweden.

Appendix

Table A1 gives the optimal variable lag selection for the stock market indices in our sample, which comprises nine Asian stock markets and the US stock market. In each case, we take the natural logarithm of the daily price of that index, employing the AIC, SBC and HQC to determine the optimal lag.

Table A1: Optimal lag selection

Lag	LogL	LR	FPE	AIC	SBC	HQC
0	14,893.13	NA	4.62e-18	-11.53	-11.51	-11.52
1	71,434.24	112,600.1	4.60e-37	-55.29	-55.04*	-55.19*
2	71,610.85	350.34*	4.34e-37*	-55.34*	-54.87	-55.17

Note: * Lag order selected based on the criterion LR test statistic, with each test at the 5 percent level.
Source: Authors' calculations based on data from Bloomberg, Investing.com and Yahoo Finance.

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The Impact of Rural Electrification on Education: A Case Study from Peru

Julio Aguirre*

Abstract

This study examines the indirect impact of rural electrification on education. It finds that the greater the likelihood of a household being connected to the electricity grid, the more time the household's children are likely to spend studying at home. This finding is interpreted as indirect evidence of an improvement in levels of schooling. Using instrumental variables to overcome endogeneity problems, the study's LATE estimates reveal that providing households with access to electricity leads to children studying an extra 94 - 137 minutes at home per day, on average.

Keywords: rural electrification, infrastructure, education, Peru.

JEL classification: O12, C31, C81.

1. Introduction

The impact of rural electrification programs has received considerable attention in the literature as well as among policymakers aiming to ensure that public resources are allocated optimally. In both cases, the conclusion is the same: rural electrification generates substantial and favorable changes in welfare and is deemed a prerequisite for economic growth. A range of studies support this idea, including Khandker et al. (2012); the Asian Development Bank (2010); Meier et al. (2010); the World Bank (2002); Cabraal, Barnes and Agarwal (2005); Martins (2005); and Barnes, Peskin and Fitzgerald (2003).

The literature divides the benefits of electricity into two categories: direct and indirect. The first includes improved lighting and the wider use of amenities such as television, radio and refrigeration. The second includes better educational outcomes, greater opportunities for income generation, lower fertility rates (Peters & Vance, 2011) and better health outcomes (by

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I am grateful to the Ministerio de Energía y Minas and the Organismo Supervisor de la Inversión en Energía y Minería in Peru for the data and geo-spatial information used in this study.

reducing indoor air pollution and enabling vaccines to be cold-stored). The Independent Evaluation Group (IEG) (2008) describes the direct impact of rural electrification in terms of improving the quality of services provided by schools that use electricity-dependent equipment, and the indirect impact in terms of increasing the time allocated to studying at home or the availability of educational programs on TV.

This study examines the impact of rural electrification on schooling by looking at the relationship between the proportion of rural households connected to the electricity grid and the time children spend studying at home. Drawing on a unique survey of energy use in Peru conducted by Urrunaga et al. (2013), the study finds that household access to electricity increases the time children spend studying at home, which can be interpreted as indirect evidence of an improvement in schooling.

Broadly, the literature supports the idea that children living in households with access to electricity are better educated than those in households with no electricity. For a sample of households in Peru, Meier et al. (2010) observe that school-going children aged 6–18 years, living in households with access to electricity, spend an average of 65 minutes reading and/or studying every evening, whereas those in households without electricity spend 51 minutes on such activities – the difference is found to be statistically significant. The IEG (2008) employs standardized demographic and health surveys carried out in nine countries and finds that, on average, access to electricity is associated with children spending more than 70 minutes a day studying at home.[1]

In 2006, Peru initiated a series of rural electrification programs under the Ley General de Electrificación (Law of General Rural Electrification). This was done in coordination with regional and local governments to provide villages (populated centers) and rural households with access to energy. The Ministerio de Energía y Minas del Perú (MEM), through the Dirección General de Electrificación Rural (DGER), established a set of criteria for targeting rural areas: (i) the coefficient of provincial rural electrification (lowest), (ii) the poverty rate (highest), (iii) the amount of the subsidy required to connect the area and (iv) the density of the population. Many rural electrification programs were implemented between 1993 and 2013, with the last one scheduled for 2008–17.[2] To date, Peru has invested

[1] Bangladesh, Ghana, Indonesia, Morocco, Nepal, Nicaragua, Peru, the Philippines and Senegal.

[2] It is important to note that these programs were carried out in populated villages, given that rural households in Peru tend to locate near the district capital or the land they cultivate. This has implications

US$278.6 million in such programs: 5,340 villages have been connected to the electricity grid and the share of rural households with electricity has increased nine-fold from 7.7 percent in 1993 to 70 percent in 2013.[3]

Between November 2012 and March 2013, the DGER-MEM carried out a study to calculate the social benefits of rural electrification to (i) determine whether public resources were being allocated efficiently, (ii) prioritize funding investments in public projects (to be implemented in 2014), (iii) facilitate the social evaluation of investments in public projects in Peru, and (iv) estimate the direct and indirect benefits of rural electrification. In accordance with the requirements of the DGER, a key component of the study was the Survey of Rural Household Energy Use (SRHEU), conducted in February 2013 (see Urrunaga et al., 2013). Figure 1 maps the locations surveyed.

The importance of accountability in rural electrification programs has increased substantially through more frequent impact evaluation studies and the use of sophisticated methodologies (Ravallion, 2008). Most studies on rural electrification show that it is correlated with development, but do not necessarily demonstrate a causal relationship or account for other variables such as household income:[4] see, for example, the World Bank (2002) on the Philippines; Madon and Oey-Gardiner (2002) on Indonesia; and Massé and Samaranayake (2002) on Sri Lanka.

The problem of endogeneity arising in the implementation of rural electrification programs makes it difficult to determine the direction of causality. Following Khandker, Barnes and Samad (2009, 2012) and Straub (2015), this study uses the instrumental variable (IV) technique to gauge the net effect of rural electrification, applied to cross-sectional data. Drawing on data from rural household surveys, Khandker et al. (2009, 2012) estimate the impact of rural electrification in Bangladesh and India, respectively. Both studies measure welfare outcomes at the household and individual levels,

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for the study's methodology in that the distance between a population center and the nearest medium-voltage pylon does not determine (or rarely so) a household's decision to settle in a particular area.

[3] According to a special report in *Diario El Comercio* (15 December 2013), these projects included the installation of (i) transmission lines (60, 138 and 220 kV) over 2,872 km, (ii) small-scale hydro and thermal generation units (150 MW) and (iii) 1,523 solar panels, as well as the extension of national grid networks and/or isolated electrical systems from which rural systems were developed (see also the National Plan for Rural Electrification for 2013–22).

[4] Straub (2015) points out that the literature fails to address the problem of endogeneity in the case of other infrastructure (transport, for instance).

including expenditure, income, energy consumption, employment, years of schooling and time spent studying.

Figure 1: Map of surveyed locations

Source: Urrunaga et al. (2013).

While Khandker et al. (2009) use the household's proximity to the nearest electricity line (within or beyond 100 feet)[5] as an IV (Bangladesh), their 2012 study uses the proportion of households in a community that have access to electricity[6] (India).[7] In the first case, they find that access to electricity increases the time boys and girls spend studying by more than six and eight minutes a day, respectively. In the second case, the corresponding increase is equal to more than an hour (and is slightly higher for girls than for boys). The instrument used here is the topographic distance between

[5] The distance variable affects whether the household is likely to use grid electricity, but not the outcomes of interest: households located within 100 feet of the electricity line face a lower (subsidized) connection cost, while those beyond 100 feet bear the full cost of connection.
[6] Peer pressure or the demonstration effect is likely to influence a household's decision to apply for a grid connection: households tend to follow the example of their neighbors.
[7] In addition to propensity score matching for Bangladesh and fixed effects for India.

each population center and the nearest medium-voltage line. The IV is correlated with each household's connection status – the shorter the distance, the greater the likelihood of a connection – but not with the time children spend studying at home.

Section 2 describes the data and econometric method used. Section 3 reports the study's results and Section 4 presents its conclusions.

2. Data and Methodology

The study draws on data from the SRHEU for 2013, spanning 987 electrified (654) and nonelectrified (333) households across 96 rural population centers in Peru.[8] The sample is probabilistic and stratified at three stages: by province, district and rural population center. The survey provides data on household composition (household size and each member's age, sex and relationship to the head of the household), levels of education, economic indicators (assets, income and expenditure) and energy use. It also measures how individuals spend their time – in this case, the number of hours children spend studying at home (see Table 1, columns 1–2).

The effects of an electricity connection can be assessed using the conceptual framework of the theory of change (see Bensch, Kluve & Peters, 2011) under which the household head's decision to apply for a grid connection is linked to a set of outcomes and impacts (for instance, poverty reduction through different channels). Columns 3–6 in Table 1 assess the extent to which the comparability of the household characteristics above translates into heterogeneity between connected and nonconnected households. The p-values in the table show that the test results for the difference in means between connected and nonconnected households are significant for most characteristics.

In focusing solely on the impact of electricity connections on the time primary school-going children spend studying at home, this outcome is treated as an intermediate measure of more tangible outcomes such as academic grades, for which there was no data available. However, it is limited by the consideration that children might also spend this time watching TV or listening to the radio (amenities that run on electricity) – notwithstanding the benefits associated with educational programs (IEG, 2008).[9] The descriptive statistics for this indicator are given in Table 1 and

[8] The survey defines a rural population center as comprising 100 contiguous dwellings.

[9] On average, more time is allocated at home to reading than to watching TV or listening to the radio (see Table A1 in the Appendix).

imply that there is a difference between connected and nonconnected households at the national level.

Table 1: Summary statistics

Variable	Mean 1	SD 2	NC 3	C 4	Diff. 5	p-value 6
Household characteristics						
Access to electricity (1 = yes, 0 = no)	0.337	0.473				
Homeownership (1 = yes, 0 = no)	0.853	0.354	0.8593 (0.3479)	0.8408 (0.3664)	0.0185	0.0000
Connected to water network (1 = yes, 0 = no)	0.400	0.490	0.3149 (0.4649)	0.5676 (0.4962)	-0.0320	0.0000
Connected to sanitation network (1 = yes, 0 = no)	0.091	0.288	0.0382 (0.1919)	0.1952 (0.3969)	-0.1569	0.0000
Concrete, wood or corrugated roof (1 = yes, 0 = no)	0.633	0.482	0.5719 (0.4952)	0.7538 (0.4315)	-0.1819	0.0000
Concrete walls (1 = yes, 0 = no)	0.082	0.275	0.0459 (0.2094)	0.1532 (0.3607)	-0.1073	0.0000
Concrete or hardwood floors (1 = yes, 0 = no)	0.323	0.468	0.2982 (0.4578)	0.3724 (0.4842)	-0.0742	0.0184
Observations	987		654		333	
Household head characteristics						
Time spent living in given population center	22.867	17.791	22.7584 (18.2324)	23.0778 (16.9200)	-0.3194	0.7907
Education level (years)	7.176	3.921	6.9931 (3.8297)	7.5360 (4.0759)	-0.5429	0.0396
Age (years)	45.409	15.013	44.2324 (14.9276)	47.7207 (14.9327)	-3.4883	0.0005
Gender (male = 1, female = 0)	0.881	0.323	0.8761 (0.3297)	0.8919 (0.3109)	-0.0157	0.4699
Household size	3.806	1.763	3.7431 (1.8183)	3.9309 (1.6441)	-0.1878	0.1136
Observations	987		654		333	
Intermediate outcome						
Time children spend studying at home (average hours per day)	4.091	2.414998	3.9198 (2.3359)	4.3731 (2.4894)	-0.4533	0.0340
Observations	542		337	205		

Note: NC = nonconnected households, C = connected households.
The sample is spread across 97 population centers in 32 districts. On average, each district comprises 3.031 population centers, with a maximum of 10 and a minimum of 1. On average, each population center includes 10.5 households, with a standard deviation of 9.3. Standard deviations are given in parentheses.
Source: Author's calculations based on data from the SRHEU for 2013.

As explained earlier, the problem of endogeneity can make such electrification programs difficult to evaluate, as comparing outcomes across connected and nonconnected households can result in biased parameters (Ravallion, 2008). The decision to connect to the electricity grid is made at the level of the individual household, and may be related to unobserved characteristics that also impact the outcome measured (Peters, 2009). For instance, households with better-educated parents are more likely to bear the cost of applying for an electricity connection because they (i) have greater financial resources *and* (ii) may assign more importance to the time children spend studying at home. This simultaneity implies that it is not necessarily possible to determine the direction of causality between a household's level of education and its connection status.

While households with access to electricity may have more opportunities available to them, this does not necessarily translate into higher levels of education for their children. Keeping in mind the endogeneity problem and the fact that grid electricity services are made available to relatively developed and densely populated regions before reaching poorer, more remote areas (Khandker et al., 2009), we need to use an IV that is correlated with a household's electricity connection status (the relevance restriction), but not with its outcome variable (the exclusion restriction).

We use the topographic distance between each population center and the nearest medium-voltage line as an instrument for being connected to the electricity grid. This measure was generated using Arcgis 10.1 software and the coordinates locating the transmission lines provided by the Organismo Supervisor de la Inversión en Energía y Minería (OSINERGMIN), which supervises investment in energy and mines in Peru.[10] The study's hypothesis is that this variable is correlated with the household's connection status – the smaller the distance, the greater the likelihood of a connection – but not with the time children spend studying at home. We use the Hausman test to gauge whether ordinary least squares (OLS) or the IV approach is the better estimation technique in this case.

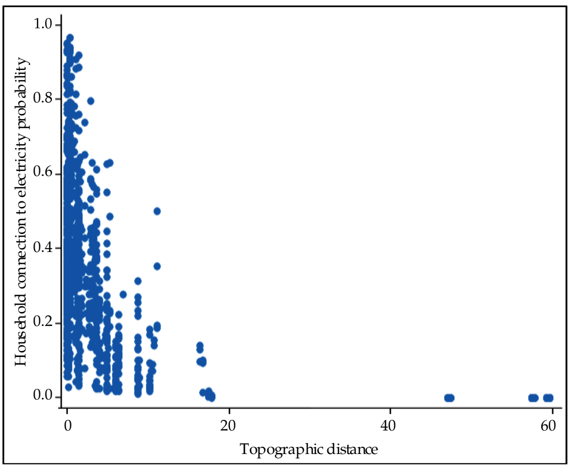
While we cannot formally test the exclusion restriction, we can examine its validity to the extent of arguing that the instrument violates this restriction, affecting the outcome variable through a channel other than access to electricity. This could include parents' propensity to spend time helping their children with schoolwork (based on their decision to live in a

[10] Table A2 in the Appendix, which gives the distances calculated, illustrates the relevance restriction.

relatively developed area) or household income (richer, more densely populated areas tend to be nearer transmission lines).[11]

To maintain the exclusion restriction, Figure 2 assumes that 'rich' and 'poor' households are both located at the same distance from the transmission lines.[12] Two caveats are worth noting here. First, the survey includes poorer, remote population centers that, in 2013, met the DGER-MEM criteria for future rural electrification programs. Second, the fieldwork revealed that some households already had access to electricity either because they were using a different source (such as solar panels) or a different (private) supplier. These caveats are assumed not to affect the study's outcomes because it looks at the impact of access to electricity in general and not that of a specific rural electrification program.

Figure 2: Electricity connections and distance from transmission lines



Source: Author's calculations.

3. Results

The causal relationship between a rural household's electricity connection status and the time its children spend studying at home is formally written as:

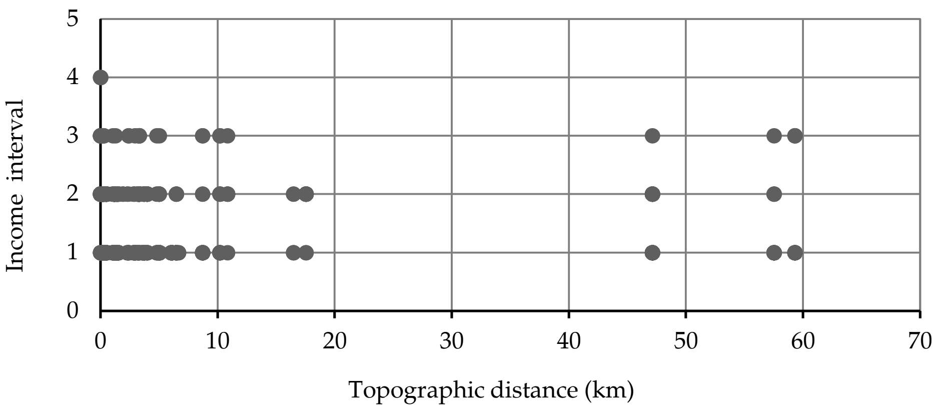
$$\text{Time spent studying by children}_{ir} = \beta + \alpha \cdot \textit{household connection status}_{ir} + \theta \cdot X_{ir} + \delta_r + \varepsilon_{ir}$$

[11] Both examples in parentheses are based on a pertinent comment from an anonymous reviewer.
[12] The density could not be calculated because there was no data available on the area (in square kilometers) covered by each population center.

where the time spent studying is measured in hours and the subscripts i and r denote the household and region, respectively. X is a vector of control variables, δ_r is the region effect, α is the average treatment effect and ε_{ipr} is an error term.

Carrying out an OLS estimation should lead to upward-biased parameters because the unobservable variables are positively correlated with the household's connection status and with the time children spend studying at home. Accordingly, we estimate the equation using two-stage least squares (2SLS), where the endogenous dummy variable 'household connection status' is instrumented by the exogenous variable 'topographic distance'. Figure 3 plots the conditional probability of each household's connection status, given the distance between the village and the nearest transmission line. The most important feature of this figure is the negative relationship between topographic distance and the likelihood of being connected to the electricity grid.

Figure 3: Income intervals, by distance



Note: Income interval = 1 for monthly incomes < US$166, 2 for monthly incomes between US$166 and US$333, 3 for monthly incomes between US$333 and US$666, 4 for monthly incomes > US$666.
Source: Author's calculations based on data from the SRHEU for 2013.

The first-stage estimates are given in Table 2. The point estimates of the coefficient of topographic distance indicate that the probability of being connected is around 18 percentage points higher for households located in villages nearer a transmission line. The first-stage effect is estimated precisely and is significantly different from 0.

Table 2: First-stage results, national level

	Dependent variable = household's electricity connection	
	(1)	**(2)**
Topographic distance	-0.1830***	-0.1823**
	(0.040)	(0.0416)
Constant	-1.3257**	-1.7403*
	(0.4387)	(0.4875)
Household and household head characteristics	Yes	Yes
Dummy regions	No	Yes
Method	Probit	Probit
Observations	537	537
Wald test	Chi-sq(11) = 83.99 Prob. > Chi-sq = 0.000	Chi-sq (13) = 102.38 Prob. > Chi-sq = 0.000

Note: Standard errors given in parentheses. * = significant at 10% level, ** = significant at 5% level, *** = significant at 1% level. Control variables: household head characteristics and household characteristics.
Source: Author's calculations based on data from the SRHEU for 2013.

The IV estimator does not yield the average treatment effect unless one is willing to assume a constant treatment effect. Under sensible assumptions, however, it yields an alternative parameter, the local average treatment effect (LATE) (see Angrist, Imbens & Rubin, 1996), which is the average effect of treatment on those individuals whose treatment status is changed by the instrument (topographic distance). This applies because households with an electricity connection have obtained one on the basis that their village is near a transmission line – they would not have been connected otherwise.[13] Thus, the results reported in the table do not need to be generalized across the population of households that, under no circumstances, would have an electricity connection.

Table 3 estimates the impact of having an electricity connection with and without the household head and household characteristics and the dummy regions. As a benchmark, it also reports the reduced-form estimates in columns 3 and 4.

[13] We assume the LATE theorem holds (Imbens & Angrist, 1994), which states that an instrument that is as good as randomly assigned (i) affects the outcome through a single known channel, (ii) has a first stage and affects the causal channel of interest only in one direction and (iii) can be used to estimate the average causal effect on the affected group (Angrist & Pischke, 2009).

Table 3: Estimates of the impact of electricity connections on the time children spend studying at home, national level

Dependent variable = time children spend studying at home (average hours/ per day)

	(1)	(2)	(3)	(4)	(5)	(6)
Household's electricity connection	0.399 (0.472)	0.739 (0.384)			1.561* (0.682)	2.289*** (0.564)
Topographic distance			-00246* (0.0099)	-0.0418*** (0.0101)		
Household and household head characteristics	Yes	Yes	No	No	Yes	Yes
Dummy regions	No	Yes	No	Yes	No	Yes
Observations	537	537	537	537	537	537
Method	OLS	OLS	OLS	OLS	2SLS	2SLS

Note: Standard errors given in parentheses. * = significant at 10% level, ** = significant at 5% level, *** = significant at 1% level. Control variables: household head characteristics and household characteristics. Models (5) and (6) use topographic distance as an IV.
Applying the Hausman test for endogeneity, the null hypothesis is rejected at 5% in all cases, confirming that 2SLS is the better method. Models (1) and (5): Chi-sq (1) = 6.39, prob. > Chi-sq = 0.0115. Models (2) and (6): Chi-sq (1) = 18.96, prob. > Chi-sq = 0.0000.
Source: Author's calculations based on data from the SRHEU for 2013.

The 2SLS estimates in columns 5 and 6 indicate that household connections to electricity significantly increase the time children spend studying at home (39.8 and 58.4 percent respectively).[14] Thus, the IV results suggest that acquiring a connection will allow children to study 93.7 (col 5) to 137.3 (col 6) additional minutes a day relative to those in households without access to electricity. The result of the Hausman test rejects the null hypothesis in these outcomes at the 5 percent level, confirming that the IV technique provides better estimates (consistent) for this sample. The table also reports the OLS results for purposes of comparison.

4. Conclusion

The study's aim was to contribute to the literature assessing the impact of rural electrification programs. Using an IV approach to overcome endogeneity concerns, it finds a positive association between rural electrification and the number of hours that school-going children spend studying at home, allowing greater opportunity for improving their academic performance. The findings suggest that the household's access to electricity (in terms of a grid connection) leads to a significant increase – of

[14] The percentage change is calculated as 100*estimate/average time spent studying by children in nonconnected households: 100*1.561/3.9198=39.8 and 100*2.289/3.9198 = 58.4.

94 to 137 minutes a day – in the time children spend studying at home. This increase is greater than the average reported by the IEG (2008) (70 minutes) and the World Bank (2000) (48 minutes); other studies such as Khandker et al. (2009) find an even smaller corresponding increase of 6–8 minutes a day for Bangladesh. The IEG study points out, however, that access to electricity can also be associated with more time spent watching TV and other forms of entertainment as opposed to studying.

Going further, the benefits of rural electrification can be approximated in monetary terms. Beltrán (2013) shows that an additional hour of study by children aged 3–12 years reduces the likelihood of their repeating a grade by 1.6 percentage points. If the yearly cost per student at rural public schools is US$2,070.70,[15] then Beltrán's estimate would imply that the government saves US$33.13 (= 2,070.7 x 0.016) annually in terms of children who have not had to repeat a year. If the measured benefit of an electricity connection at the national level is 1.56 – 2.29 extra hours that children spend studying at home, then the benefit to a rural household that chooses to connect to the electricity grid amounts to US$51.68 (= 1.56 x 33.13) to US$75.87 (=2.29 x 33.13) per child. Of course, other benefits of rural electrification, such as better lighting and access to amenities such as radio/TV and refrigeration, could also be added to this.[16]

This cross-sectional analysis has two shortcomings. First, the survey used was conducted during December to March, which overlaps with term breaks. This may have led to biased answers concerning the time children report studying at home. Second, given the time constraint involved, the survey could not collect data on other dependent variables that measure schooling outcomes such as numeracy, reading skills and the extent to which exposure to radio and TV facilitates language learning. Finally, the current extent of rural electrification coverage – 78 percent, as reported by the MEM (2015) – implies there is still room for expanding access to electricity, especially given the potential impact of this expansion on meeting the education-related Millennium Development Goals.

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[15] Based on data from the education ministry (http://escale.minedu.gob.pe/) and an exchange rate of PEN2.8 per US$1.0.

[16] See Urrunaga et al. (2013), who calculate the cost of providing rural electrification were calculated considering benefits of illumination and radio & TV (using consumer excedent and avoided costs methodologies) and of education (using matching techniques),

References

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*, *91*(434), 444–455.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton University Press.

Asian Development Bank. (2010). *Asian Development Bank's assistance for rural electrification in Bhutan – Does electrification improve the quality of rural life?* (IES No. BHU 2010-27). Manila: Author.

Barnes, D. F., Peskin, H. M., & Fitzgerald, K. (2003). *The benefits of rural electrification in India: Implications for education, household lighting and irrigation*. Unpublished manuscript, World Bank, Washington, DC.

Beltrán, A. (2013). El tiempo de la familia es un recurso escaso: ¿Cómo afecta su distribución el desempeño escolar? *Apuntes Revista de Ciencias Sociales*, *40*(72), 117–156.

Bensch, G., Kluve, J., & Peters, J. (2011). *Impacts of rural electrification in Rwanda* (Discussion Paper No. 6195). Bonn: Institute for the Study of Labor.

Cabraal, R. A., Barnes, D. F., & Agarwal, S. G. (2005). Productive uses of energy for rural development. *Annual Review of Environment and Resources*, *30*, 117–144.

Imbens, G. W., & Angrist, J. D. (1994). Identification and estimation of local average treatment effects. *Econometrica*, *62*(2), 467–476.

Independent Evaluation Group. (2008). *The welfare impact of rural electrification: A reassessment of the costs and benefits*. Washington, DC: World Bank.

Khandker, S., Barnes, D. F., & Samad, H. A. (2009). *Welfare impacts of rural electrification: A case study from Bangladesh* (Policy Research Working Paper No. 4859). Washington, DC: World Bank.

Khandker, S., Barnes, D. F., & Samad, H. A. (2013). Welfare impacts of rural electrification: A panel data analysis from Vietnam. *Economic Development and Cultural Change*, *61*(3), 659–692.

Khandker, S., Samad, H. A., Ali, R., & Barnes, D. F. (2012). *Who benefits most from rural electrification? Evidence in India* (Policy Research Working Paper No. 6095). Washington, DC: World Bank.

Madon, G., & Oey-Gardiner, M. (2002). EnPoGen study in Indonesia. *ENERGIA News*, *5*(3), 11–13.

Martins, J. (2005). The impact of the use of energy sources on the quality of life of poor communities. *Social Indicators Research*, *72*(3), 373–402.

Massé, R., & Samaranayake, M. R. (2002). EnPoGen study in Sri Lanka. *ENERGIA News*, *5*(3), 14–16.

Meier, P., Tuntivate, V., Barnes, D. F., … Farchy, D. (2010). *Peru: National survey of rural household energy use* (Energy and Poverty Special Report No. 007/10). Washington, DC: World Bank.

Ministerio de Energía y Minas del Perú. (2015). *Plan nacional de electrificación rural (PNER): Periodo 2016–2025*. Lima: Dirección General de Electrificación Rural.

Peters, J. (2009). Evaluating rural electrification projects: Methodological approaches. *Well-Being and Social Policy*, *5*(2), 25–40.

Peters, J., & Vance, C. (2011). Rural electrification and fertility: Evidence from Côte d'Ivoire. *Journal of Development Studies*, *47*(5), 753–766.

Ravallion, M. (2008). Evaluating anti-poverty programs. In T. P. Schultz & J. Strauss (Eds.), *Handbook of development economics*, vol. 4 (chap. 59). Amsterdam: North-Holland.

Straub, S. (2015). Policy lessons from the recent literature on transport infrastructure development. In A. Picot, M. Florio, N. Grove & J. Kranz (Eds.), *The economics of infrastructure provisioning: The changing role of the state* (pp. 267–284). Cambridge, MA: MIT Press.

Urrunaga, R., Bonifaz, J. L., Aguirre, J., Aragón, G., & Jara, O. (2013). *Beneficios sociales de la electrificación rural: Metodologías y estimaciones* (Documento de Trabajo 91). Lima: Universidad del Pacífico, Centro de Investigación.

World Bank. (2000). *Reducing the cost of grid extension for rural electrification* (ESMAP Report No. 227). Washington, DC: Author.

World Bank. (2002). *Rural electrification and development in the Philippines: Measuring the social and economic benefits* (ESMAP Report No. 255). Washington, DC: Author.

Appendix

Table A1: Time allocated to reading, TV and radio

Variable (hours spent)	With connection	Without connection	p-value
Reading	4.565000	3.504132	0.0000
Watching TV	2.521531	2.283784	0.1306
Listening to the radio	1.733333	2.306931	0.0004

Source: Author's calculations.

Table A2: Calculation of topographic distances

Department	Province	District	Population center	Distance (km)
Apurimac	Abancay	Abancay	Atunpata	0.03
Apurimac	Abancay	Abancay	Quisapata	3.72
Apurimac	Abancay	Abancay	Wiracochapata	1.60
Arequipa	Caraveli	Acari	Lucasi	1.40
Arequipa	Caraveli	Acari	Santa Teresa	1.14
Arequipa	Caraveli	Atico	Chorrillos	10.85
Arequipa	Caraveli	Bella Union	San Isidro	0.00
Arequipa	Caraveli	Lomas	Costa Azul	0.01
Arequipa	Caraveli	Lomas	Santa Sarita	0.01
Arequipa	Caraveli	Yauca	Alto Tupac	0.01
Arequipa	Caraveli	Yauca	Yauca	0.01
Cajamarca	San Marcos	Ichocan	Illuca	6.48
Cajamarca	San Marcos	Ichocan	Llanupacha	0.10
Cajamarca	San Marcos	Ichocan	Paucamarca	3.73
Cajamarca	San Marcos	Ichocan	Paucamayo	3.58
Cajamarca	San Marcos	Ichocan	Poroporito	0.08
Cajamarca	San Marcos	Pedro Galvez	Catagon	0.40
Cajamarca	San Marcos	Pedro Galvez	Pomabamba	2.84
Cajamarca	San Marcos	Pedro Galvez	Rancho Grande	0.04
Cajamarca	San Miguel	Catilluc	Catilluc	0.52
Cajamarca	San Miguel	Catilluc	Catilluc Bajo	0.20
Cuzco	Paucartambo	Caicay	Ccollataro	0.06
Cuzco	Paucartambo	Paucartambo	Phuyucalla	0.02
Huancavelica	Tayacaja	Acraquia	Mucuro	2.30
Huancavelica	Tayacaja	Acraquia	Pamuri	0.04
Huancavelica	Tayacaja	Acraquia	San Cristobal	0.13
Huancavelica	Tayacaja	Acraquia	Tomanya	0.06
Huancavelica	Tayacaja	Salcabamba	Caymo	0.06
Huancavelica	Tayacaja	Salcabamba	Garcia Pampa	1.33

Department	Province	District	Population center	Distance (km)
Huanuco	Huamalies	Jacas Grande	Nuevas Flores	0.20
Huanuco	Huamalies	Llata	Buena Vista	5.02
Huanuco	Huamalies	Llata	Libertad	0.46
Huanuco	Huamalies	Llata	Ocshash	0.01
Huanuco	Huamalies	Llata	Sacuatuna	1.34
Ica	Chincha	Chincha Baja	Salinas	0.02
Ica	Chincha	Chincha Baja	Valencia	0.00
Ica	Chincha	Chincha Baja	Vilma Leon	0.01
Ica	Pisco	Independencia	Cabeza De Toro Lateral 6	1.47
Ica	Pisco	Independencia	Fermin Tanguis	1.47
Ica	Pisco	Independencia	Nuevo Huanuco	1.47
Junin	Satipo	Mazamari	Los Angeles De Eden Alto	0.01
Junin	Satipo	Mazamari	Materiato	1.28
Junin	Satipo	Mazamari	Mirador De Cañete	0.15
Junin	Satipo	Mazamari	San Vicente De Cañete	0.10
Junin	Satipo	Rio Negro	Bajo Huahuari	0.31
Junin	Satipo	Rio Negro	Centro Hauhuari	0.16
Junin	Satipo	Rio Negro	Centro Huahuari	0.16
Junin	Satipo	Rio Negro	Santa Rosa De Panakiari	1.53
Junin	Satipo	Satipo	Alto Capiro	0.25
Loreto	M. Ramon Castilla	Caballococha	Bufeo Cocha	8.72
Loreto	M. Ramon Castilla	Caballococha	Nuevo Palestina	6.03
Loreto	M. Ramon Castilla	Yavari	Fujimori	59.31
Loreto	M. Ramon Castilla	Yavari	Rondinha Zona I	57.53
Loreto	M. Ramon Castilla	Yavari	Santa Rosa	47.15
Pasco	Oxapampa	Oxapampa	Arcuzazu	0.04
Pasco	Oxapampa	Oxapampa	El Abra	0.50
Pasco	Oxapampa	Oxapampa	Quillazu	0.40
Piura	Sullana	Lancones	El Cortezo	0.30
Piura	Sullana	Lancones	Pampas Quemadas	3.20
Piura	Sullana	Lancones	Sausal	5.00
Piura	Sullana	Sullana	Cieneguillo Norte	1.92
Piura	Sullana	Sullana	Las Lomas	1.21
Piura	Sullana	Sullana	Las Mercedes	0.04
Piura	Sullana	Sullana	San Juan De Los Ranchos	16.48
Piura	Sullana	Sullana	Santa Rosa	3.30
Piura	Sullana	Sullana	Tres Compuertas	0.04

Department	Province	District	Population center	Distance (km)
Puno	Huancane	Cojata	Bellapampa	4.82
Puno	Huancane	Cojata	Tomapirhua	2.41
Puno	Huancane	Huancane	Bellapampa	4.82
Puno	Huancane	Huancane	Chacacruz	0.01
Puno	Huancane	Huancane	Taurahuta	0.03
Puno	Huancane	Huatasani	Catarani	6.68
Puno	Huancane	Huatasani	Ccancco	1.28
Puno	Huancane	Huatasani	Curupampa	6.10
Puno	Huancane	Huatasani	Huatapata	1.28
Puno	Huancane	Huatasani	Llinquipata	0.46
Puno	Huancane	Huatasani	Quencha Milliraya	0.05
Puno	Huancane	Huatasani	San Calvario Pongoni	1.63
Puno	Huancane	Huatasani	Tintapata	1.07
San Martin	Rioja	Nueva Cajamarca	Angaiza	0.20
San Martin	Rioja	Nueva Cajamarca	La Primavera	1.45
San Martin	Rioja	Nueva Cajamarca	Palestina	0.12
San Martin	Rioja	Nueva Cajamarca	Vista Alegre	0.03
San Martin	Rioja	Pardo Miguel	El Afluente	10.19
San Martin	Rioja	Pardo Miguel	San Juan Del Mayo	2.95
Ucayali	Coronel Portillo	Yarinacocha	11 De Agosto	1.00
Ucayali	Coronel Portillo	Yarinacocha	Aahh La Capirona	0.06
Ucayali	Coronel Portillo	Yarinacocha	Aahh Monterrico	0.06
Ucayali	Coronel Portillo	Yarinacocha	Jose Olaya	0.23
Ucayali	Coronel Portillo	Yarinacocha	Las Damas De Milagro	0.06
Ucayali	Coronel Portillo	Yarinacocha	San Francisco	0.23
Ucayali	Coronel Portillo	Yarinacocha	San Jose	0.00
Ucayali	Coronel Portillo	Yarinacocha	San Juan	0.01
Ucayali	Coronel Portillo	Yarinacocha	San Lorenzo	0.30
Ucayali	Coronel Portillo	Yarinacocha	Santa Rosa	0.10
Ucayali	Padre Abad	Curimana	Arenal Grande	17.55
Ucayali	Padre Abad	Curimana	Arenalillo	17.55
Ucayali	Padre Abad	Curimana	Sol Naciente	4.00

Source: OSINERGMIN.

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Deprivation Counts: An Assessment of Energy Poverty in Pakistan

Rafat Mahmood* and Anwar Shah**

Abstract

This paper examines the energy–poverty nexus in Pakistan at the national and provincial level, using the multidimensional energy poverty index. Based on data from the Pakistan Social and Living Standards Measurement Survey for 2010/11, we find that the average household in Pakistan is 26.4 percent energy-poor. The study shows that the incidence of energy poverty is higher in rural areas than in urban areas, with a similar trend at the provincial level. A comparison with findings based on data from 2008/09 shows a slight decrease in energy poverty at the national level.

Keywords: energy, poverty, households, Pakistan.

JEL classification: Q01.

1. Introduction

The notion of development goes hand in hand with the concept of sustainability: the use of resources for development by one generation such that it does not encroach on the prospects of the next (World Commission on Environment and Development, 1987). Munasinghe (1992) refers to this as 'sustainomics' and points out that sustainability in development must take into account three key perspectives: economic, social and environmental. Energy, as a building block of development, cuts across all three aspects (Goldemberg & Johansson, 1995). Not only is it an input to the production function, necessary for economic growth (Hu & Hu, 2013), but it is also a basic human need (Bravo et al., 1983) and essential for maintaining a minimum standard of living. Accordingly, those Millennium Development Goals (MDGs) that did not incorporate energy use were revisited – a country's ability to meet its energy requirements was seen as a prerequisite for achieving the MDGs (World Bank, 2002).

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A number of studies examine the relationship between energy and development at the household level. The use of modern cooking fuels (gas and electricity) is associated with better health, particularly among women and children, and a lower burden of disease (van der Klaauw & Wang, 2003; Smith, Mehta & Maeusezahl-Feuz, 2004). It also spares household members from having to collect traditional fuels such as wood or dung, giving them more time to spend on productive activities that lead to income generation, education and empowerment (United Nations Millennium Project 2005; United Nations Development Programme, 2000; Schultz, 1990). Similarly, the use of modern fuels to provide light plays a positive role in promoting education, health and communication (Fitzgerald, Barnes & McGranahan, 1990; Department for International Development, 2002). Finally, modern energy sources improve environmental sustainability by reducing deforestation and enhancing energy efficiency (Leach and Mearns, 1988; Sarin, 1991).

The relationship between energy and development implies that it is important to track people's energy profiles across different dimensions and over time. This makes it possible to monitor changes in energy use and assess policy effectiveness. The multidimensional nature of the energy sector calls for indicators that can gauge overall progress but also make temporal and spatial comparisons. For a developing country such as Pakistan, where per capita energy consumption is far below that of comparable countries, it is necessary to assess the current situation and identify which areas need priority,[1] given that Awan, Sher and Abbas (2013) have observed alarming levels of energy deprivation in the country.

This study employs a measure of energy poverty that takes into account a range of dimensions and has been adapted to suit Pakistan's case. We focus on energy deprivation rather than access to energy and estimate energy poverty both at the national and provincial levels as well as in rural and urban areas for the period 2008/09 to 2010/11. Section 2 looks at the literature on measures of energy poverty. Section 3 describes the study's methodology. Section 4 presents our results, accompanied by a discussion. Section 5 concludes the study.

[1] Pakistan's per capita energy use was 482 kg of oil-equivalent in 2011 compared to India (614 kg of oil-equivalent), Indonesia (857 kg of oil-equivalent) and Iran (2,813 kg of oil-equivalent) (International Energy Agency Statistics).

2. Measures of Energy Poverty

Nussbaumer, Bazilian and Modi (2012) classify measures of poverty and development as (i) single indicators (such as the world poverty line), (ii) sets of individual indicators (such as the MDG indicators and energy indicators of sustainable development) or (iii) composite indices (such as the human development index and energy for development index). While single indicators generally fail to capture all dimensions of an issue as broad as energy poverty, sets of indicators lack insight into the overall state of affairs. Composite indices are thus more valuable in that they reflect multiple facets of a problem without losing the overall picture. Developing a representative composite index is, however, not easy: the more difficult it is to define and measure a problem, the less definitive its composite index is likely to be.

While some measures of energy poverty assume that income or general poverty necessarily begets energy poverty (Foster, Tre & Wodon, 2000), the two are not always highly correlated (Pachauri & Spreng, 2004; Pachauri et al., 2004). Other studies have, therefore, defined a separate poverty line for energy. For example, Barnes, Khandker and Samad (2011) define the level of energy demand that remains invariant to income as the minimum energy needed to subsist. However, this income-invariant property of energy demand is hard to imagine, even with respect to lower-income households.

Pachauri et al. (2004) conduct a two-dimensional analysis of energy poverty that accounts for access to certain modes of energy and levels of consumption, but this approach is still too narrow. The International Atomic Energy Agency (2005) has devised an energy development index – on the lines of the human development index – that includes four dimensions of access to energy and allows cross-country comparisons. At the national level, however, the index loses its specificity with regard to energy inequality within a country and the percentage of people deemed energy-poor.

Comparing intra-country energy poverty in Punjab, Mirza and Szirmai (2010) define the energy poverty index as the arithmetic mean of the energy inconvenience and energy shortfall indices. They find that 91.7 percent of rural households in Punjab are extremely energy-poor. The wider applicability of this measure, however, requires more data, which is costly to collect.

A simpler, more comprehensive index that builds on the available data and is used to make international comparisons is the multidimensional energy poverty index (MEPI) developed by Nussbaumer et al. (2012). It captures five dimensions of energy deprivation using six indicators: modern cooking fuel, lighting, services provided by household appliances, entertainment/education and communication. A household is thus considered energy-poor if its MEPI exceeds an acceptable minimum level of deprivation.

Using the Demographic and Health Survey dataset for 2006/07, Nussbaumer et al. (2013) show that Pakistan's MEPI is 0.45 on a scale of 0 to 1. They calculate an energy poverty headcount of 0.69 and deprivation intensity of 0.66. However, the data available does not allow for temporal and provincial comparisons of energy poverty in this case. Awan et al. (2013) use the MEPI to measure energy poverty in Pakistan based on data from the Pakistan Social and Living Standards Measurement Survey (PSLM) for 2007/08. They find that 54.6 percent of households are energy-poor, where the incidence of energy poverty is higher in rural areas than in urban ones.

In measuring energy poverty in Pakistan, this study adapts the MEPI indicators to the availability of data and country-specific characteristics. This yields a wider spatial as well as temporal picture and enables us to make important comparisons by area. The model introduces dimensions of energy that previous studies have not looked at. It also compares energy poverty across the four provinces as well as their rural and urban areas for two periods.

3. Data and Methodology

The study uses data from the Pakistan Social and Living Standards Measurement Survey (PSLM) for 2008/09 and 2010/11.[2] The survey is conducted by the Pakistan Bureau of Statistics every other year to track Pakistan's performance against poverty alleviation indicators and the MDG targets. The survey is conducted in both rural and urban areas across the four provinces and the capital, Islamabad, using a two-stage stratified sampling technique. Our sample comprises 75,126 households for 2008/09 and 76,546 households for 2010/11. The PSLM's sampling method ensures an appropriate degree of provincial and regional representation.

[2] While an analysis going further back may have raised some interesting insights, earlier rounds of the PSLM do not include data for some of the dimensions we have considered.

The energy deprivation index is calculated by gauging the extent of poverty under five headings – cooking, lighting, mobility, services and space temperature regulation – using six indicators (Table 1). The deprivation index measures the extent to which a household is deprived of a certain aspect of energy. The sum of deprivation values for each dimension yields a deprivation count for the household, where a value of 1 means it is deprived of all these dimensions and a value of 0 means it is not deprived of any dimension.

Next, we determine the energy poverty line, assuming that households with a deprivation count below this threshold maintain a minimum standard of living while those with a deprivation count above the threshold are deemed energy-poor. For instance, if a household is deprived of a single dimension, it may not necessarily be energy-poor, but if it is deprived of more than one dimension, then it is likely to have a compromised standard of living. The weight assigned to any one dimension is 0.2, with a cut-off point of 0.3 – if the deprivation count of a household is less than 0.3, it is considered nonpoor whereas a count greater than or equal to 0.3 indicates that the household is energy-poor.

Table 1: Construction of deprivation index

Dimension		**Indicator**		**HIES questionnaire section**	**Deprivation criteria for household**
Type	Weight	Type	Weight		
Cooking	0.2	Modern fuel for cooking	0.2	G	Uses anything other than modern cooking fuel (electricity, gas, kerosene oil)
Lighting	0.2	Electricity access	0.2	G	Uses anything other than electricity as main source of lighting
Mobility	0.2	Means of transportatio n	0.2	F and G	Does not own vehicle The nearest public transport is more than 14 minutes on foot
Space temperature regulation	0.2	Fan	0.2	F	Does not own a fan
Services	0.2	Refrigerator	0.1	F	Does not own a refrigerator
		TV/radio	0.1	F	Owns neither a TV nor radio

Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

The MEPI is defined as the product of the headcount of all energy-poor households (H) and the average intensity of poverty (A). Specifically, given a total of n households of which p are found to be energy-poor:

$$H = \frac{p}{n} \tag{1}$$

Similarly, if the deprivation count for each household i is c_i, then A is calculated as follows:

$$A = \frac{\sum_{i=1}^{n} c_i}{p} \tag{2}$$

Next, we calculate the MEPI:

$$MEPI = H * A \tag{3}$$

The value of the MEPI lies between 0 and 1: the higher the score on the index, the greater is the level of deprivation.

It is worth discussing how this study has modified the index used by Nussbaumer et al. (2012). One significant change is the addition of two dimensions of energy use: mobility and space temperature regulation. While the literature acknowledges their importance (see, for example, Sovacool et al., 2012), they are missing from the original index for want of sufficient data. In this case, however, the PSLM provides data on transport means and household ownership of an electric fan, which represent mobility and the ability to regulate space temperature, respectively. This generates a more representative index of energy deprivation for Pakistan. Thus, households that do not own any means of transport (a bicycle, motorcycle or car/truck) and are more than 14 minutes away from the nearest source of public transport are deemed energy-deprived in terms of mobility. Households that own an electric fan would be considered energy-nonpoor in terms of space temperature regulation.[3]

In addition, Nussbaumer et al. (2012) use two indicators to measure energy use for cooking: modern cooking fuels and indoor pollution (gauged by whether food is cooked on a stove or over an open fire using traditional

[3] Originally, the indicator was intended to measure household ownership of either a fan or a heater to take into account areas that were too cold to need fans or too hot to need heaters. However, the PSLM lacks data on the latter, which meant we could not include household ownership of a heater in this study. An analysis of data from the Household Integrated Economic Survey for 2010/11 revealed that only 0.58 percent of households owned a heater but not a fan, making it viable to drop ownership of a heater from the space temperature regulation indicator.

fuels). Our analysis does not include the second indicator: we assume that households that use modern fuels for cooking must own a stove for this purpose. Moreover, there is no data on the kind of stove being used (i.e., whether it has an exhaust and, therefore, causes less indoor pollution).

Nussbaumer et al. (2012) use telecommunication means (a landline or mobile phone) to measure the energy used for communication. We drop this dimension on the grounds that landline telephones do not require energy, making the indicator less relevant. Instead, we use ownership of a television/radio as a proxy for both communication and entertainment, combining this with ownership of a refrigerator to reflect the broad dimension of 'services' provided by energy. Finally, we assume that all five dimensions carry equal weight because they are all essential to maintaining a minimum standard of living. The 'services' dimension is assessed using two equally weighted indicators.[4]

4. Results and Discussion

This section presents our results for the level of energy deprivation based on the MEPI.

4.1. MEPI Scores Across Pakistan

On a scale of 0 to 1, the national MEPI for 2010/11 is 0.264. This shows that each household in Pakistan is, on average, 26.4 percent energy-deprived (Figure 1).[5] Put another way, if maintaining an acceptable standard of living requires 100 percent of the basic energy needs basket, then the average Pakistani household is unable to meet 26.4 percent of its needs. Since this value does not reflect the proportion of energy-poor households, we calculate H, which is equal to 56.2 percent. This implies that more than half the households in Pakistan are energy-poor. When we calculate the energy deprivation level (A) for this proportion, we find that, on average, each energy-poor household falls short of meeting its basic energy needs by 47.1 percent. These findings indicate that more than half the households in Pakistan are energy-poor (H = 56.2 percent) and face a very high deprivation level (A = 47.1 percent).

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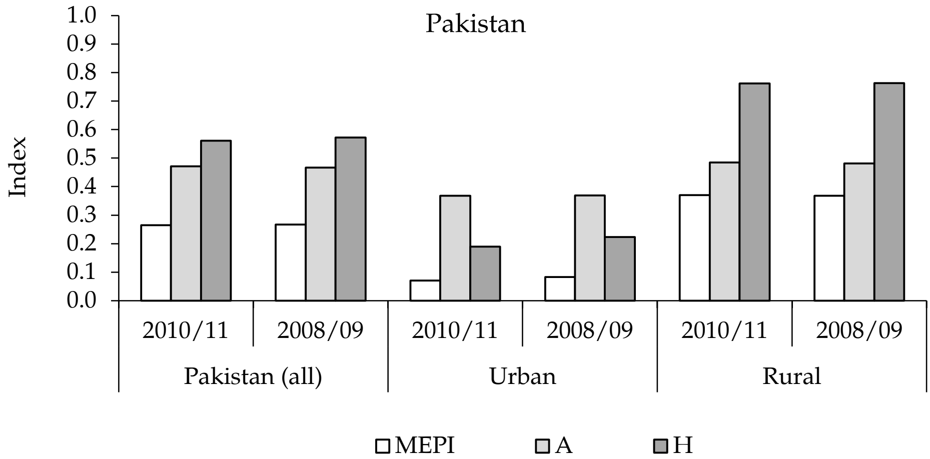
[4] We do not use principal component analysis to assign weights because it would do so based on the covariance matrix of each variable, intending to make the index more representative of the original data. Our aim, however, is to assign weights to variables according to their importance as a dimension of energy poverty. While this is a more subjective approach, it is also more relevant to the study's aims.

[5] See Table A1 in the Appendix for the tabulated results.

Figure 1: MEPI, energy poverty intensity and headcount



Note: A = energy deprivation level, H = proportion of energy-poor households.
Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

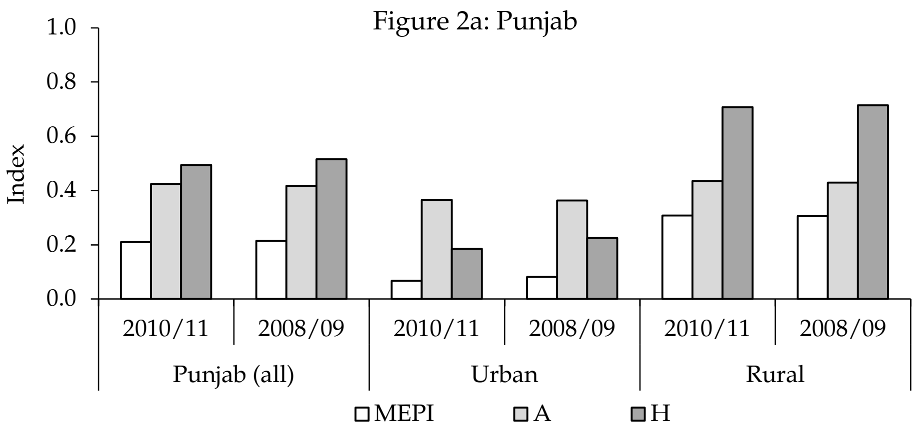
Figure 1 also illustrates the MEPI for rural and urban Pakistan. On average, urban areas fare better, with a MEPI of 7 percent relative to 36.9 percent for rural areas in 2010/11.[6] The proportion of energy-poor households (H) is 19 percent in urban Pakistan and 76.2 percent in rural Pakistan, with deprivation levels (A) of 36.8 and 48.5 percent, respectively. Overall, not only are a significant number of rural households energy-poor, but they are also unable to benefit from the larger pool of energy-related services available to energy-poor households in urban areas.

4.2. MEPI Scores by Province

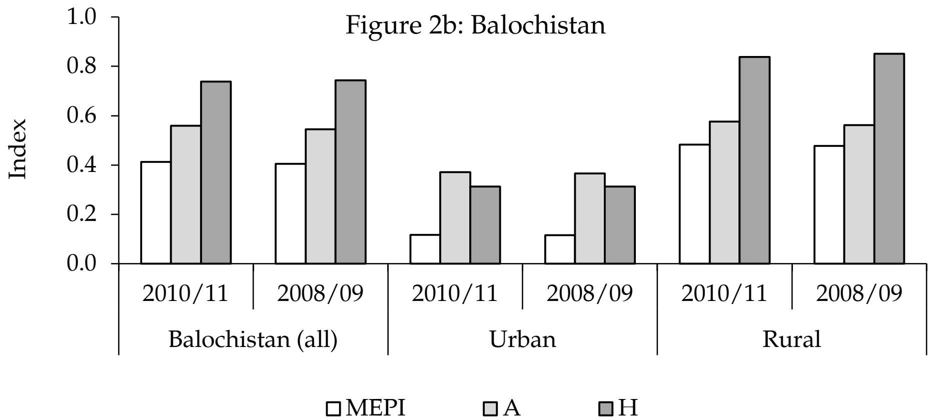
The deprivation index for the provinces is shown in Figure 2 (a–d). Overall, Punjab fares best with a MEPI of around 21 percent, followed by Sindh (24.9 percent) and Khyber Pakhtunkhwa (KP) (29 percent). Balochistan has the highest deprivation index at 41.3 percent. The proportion of energy-poor households (H) follows a similar pattern. Balochistan accounts for the largest share of energy-poor households (73.8 percent), followed by KP (60.3 percent). Punjab and Sindh have a far smaller share of energy-poor households: 49.4 percent and 52.6 percent, respectively.

[6] The MEPI values we have calculated are not comparable with those in Nussbaumer et al. (2013) because of differences in the methodology employed.

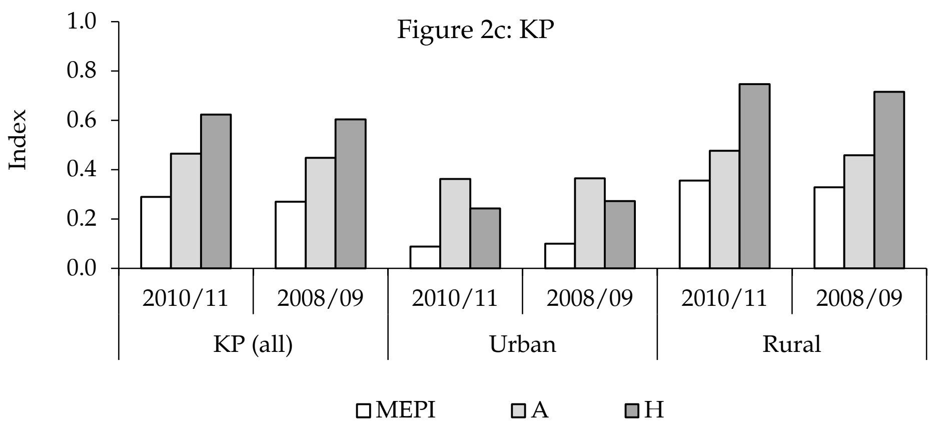
Figure 2: MEPI, energy poverty intensity and headcount, by province



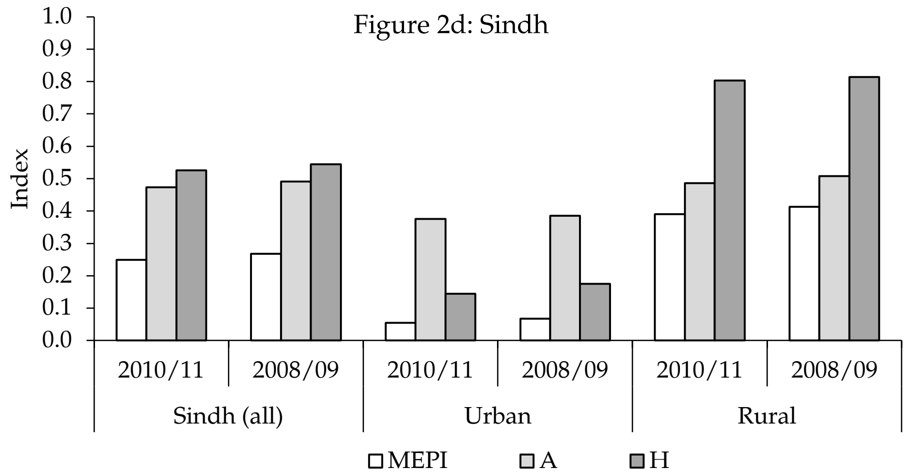
Note: A = energy deprivation level, H = proportion of energy-poor households.



Note: A = energy deprivation level, H = proportion of energy-poor households.



Note: A = energy deprivation level, H = proportion of energy-poor households.



Note: A = energy deprivation level, H = proportion of energy-poor households.

Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

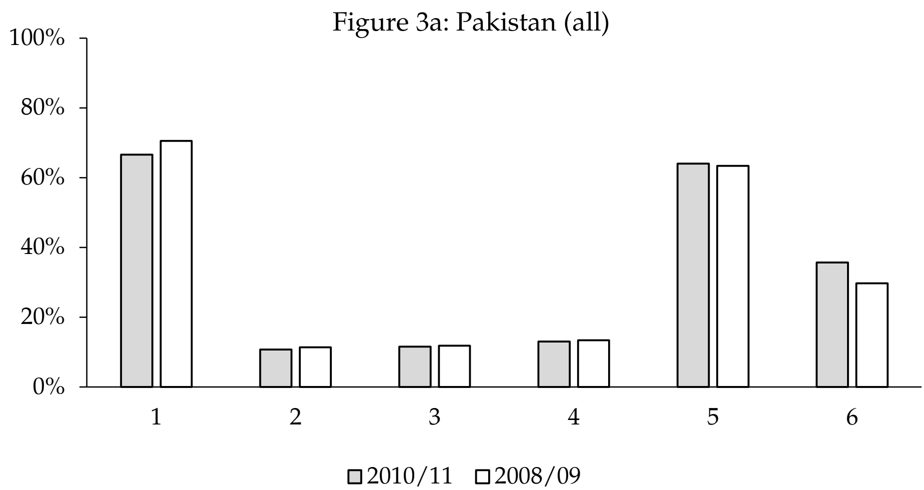
A slightly different pattern emerges when we calculate the deprivation levels (A) for each province. The energy deprivation level of energy-poor households is highest in Balochistan (55.9 percent), followed by Sindh (47.3 percent), KP (46.5 percent) and Punjab (42.5 percent). Thus, while Sindh has fewer energy-poor households than KP, those in Sindh are deprived of more energy-related services than in KP.

Figure 2 also compares MEPI scores across rural and urban areas in each province. Overall, there is a significant rural-urban difference. The proportion of energy-poor households (H) in urban and rural Punjab is 18.5 and 70.7 percent, respectively. The corresponding ratios are 14.4 and 80.3 percent in Sindh, 24.3 and 74.6 percent in KP, and 31.3 and 83.9 percent in Balochistan. The intensity of deprivation (A) in urban Punjab is 36.6 percent relative to 43.5 percent in rural parts of the province. Urban Sindh has a deprivation level of 37.5 percent compared to 48.6 percent in rural Sindh. The corresponding values of A are 36.2 and 47.6 percent for urban and rural KP, and 47.0 and 57.6 percent for urban and rural Balochistan.

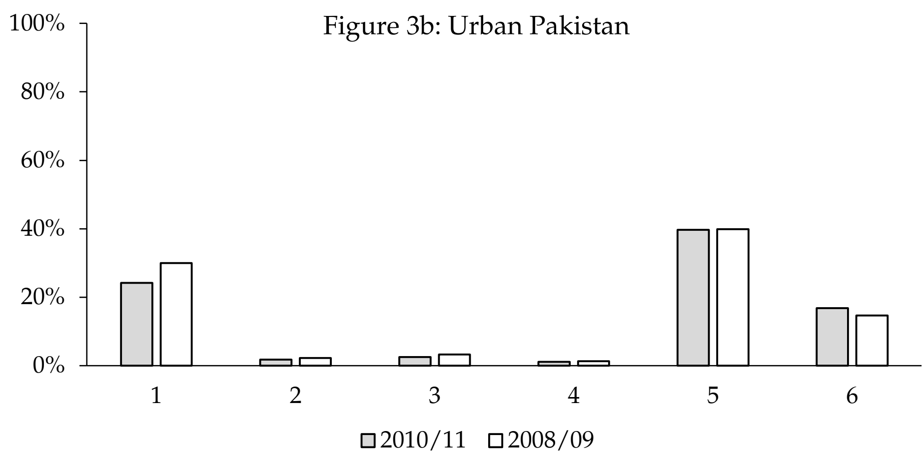
4.3. Dimensions of Energy Poverty

Breaking down the index into its five components yields useful insights in terms of their relative importance. Figures 3 (a–c) and 4 (a–l) illustrate this for Pakistan and the four provinces.[7]

Figure 3: Distribution of energy-poor households, by energy poverty and urban/rural status

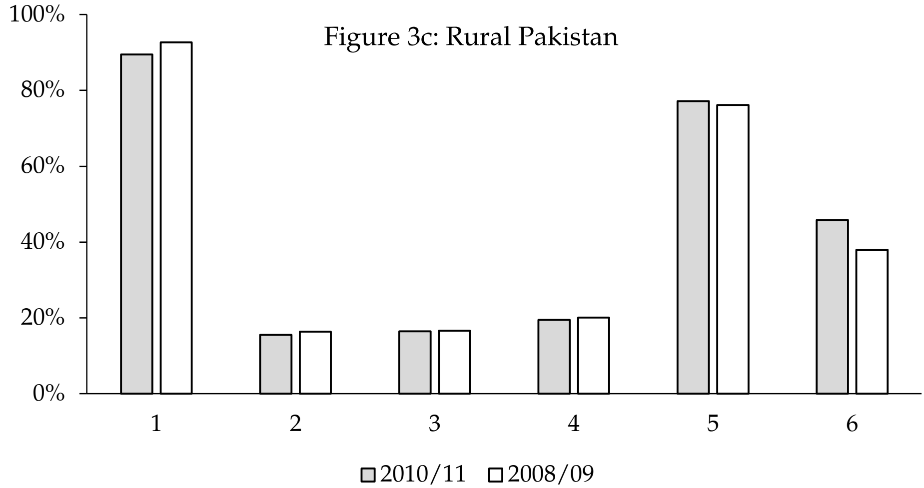


Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.



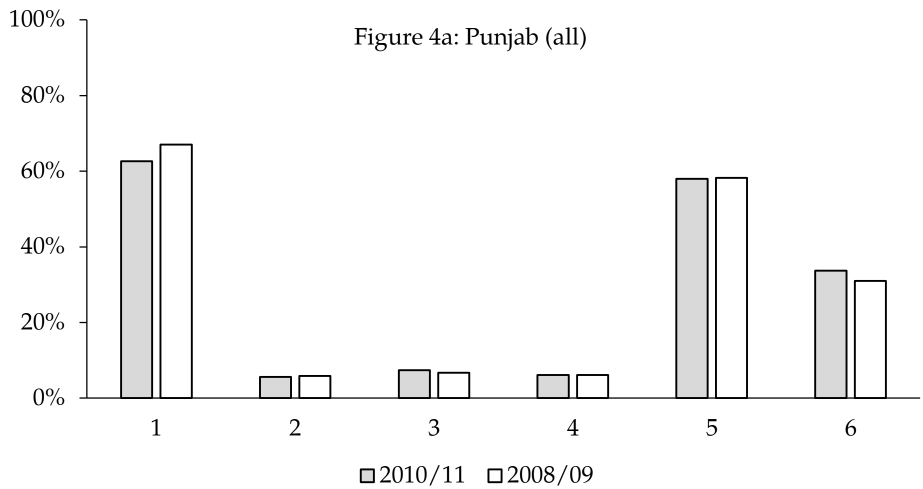
Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

[7] See Table A2 in the Appendix for the tabulated results.



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.
Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

Figure 4: Distribution of energy-poor households, by energy poverty, province and urban/rural status



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

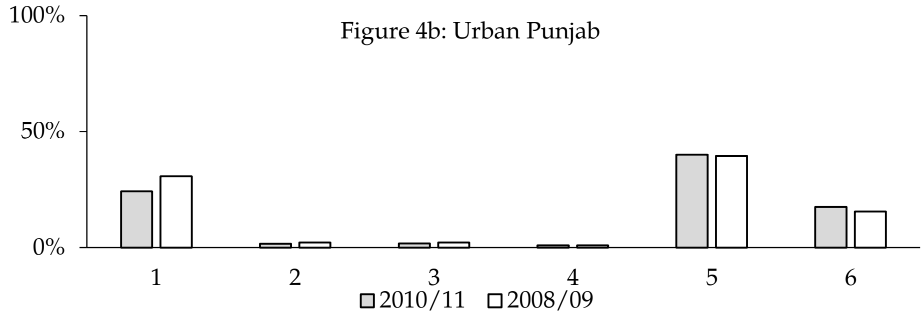


Figure 4b: Urban Punjab

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

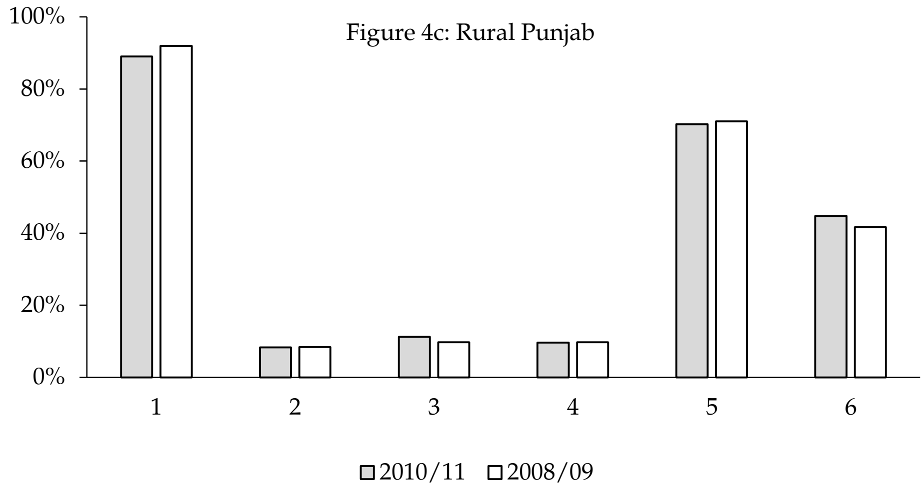


Figure 4c: Rural Punjab

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

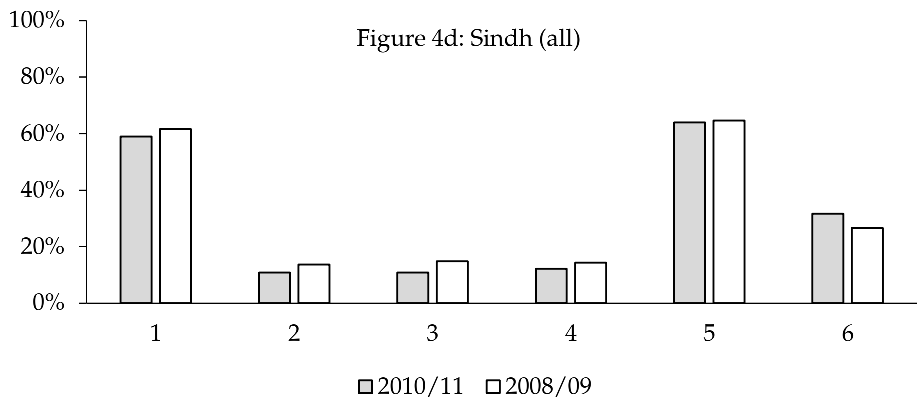
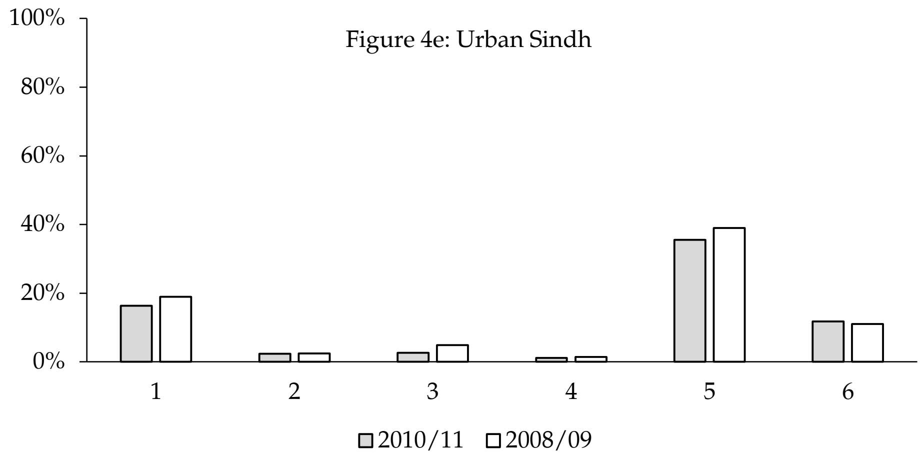
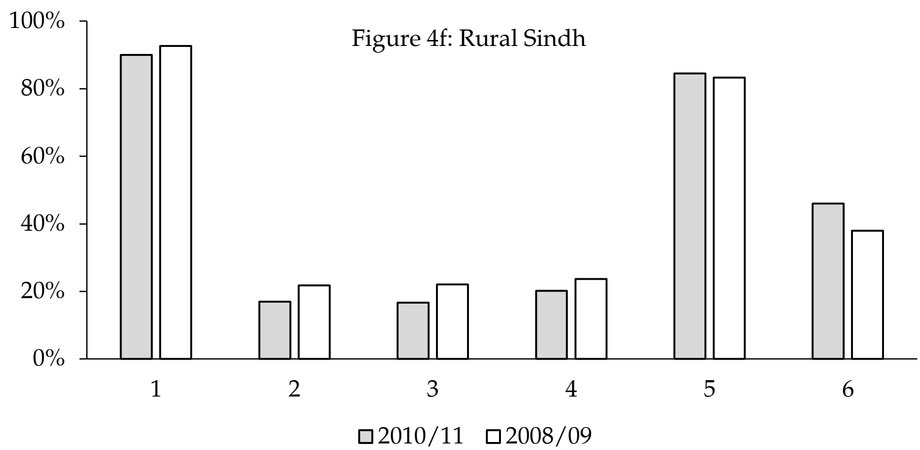


Figure 4d: Sindh (all)

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

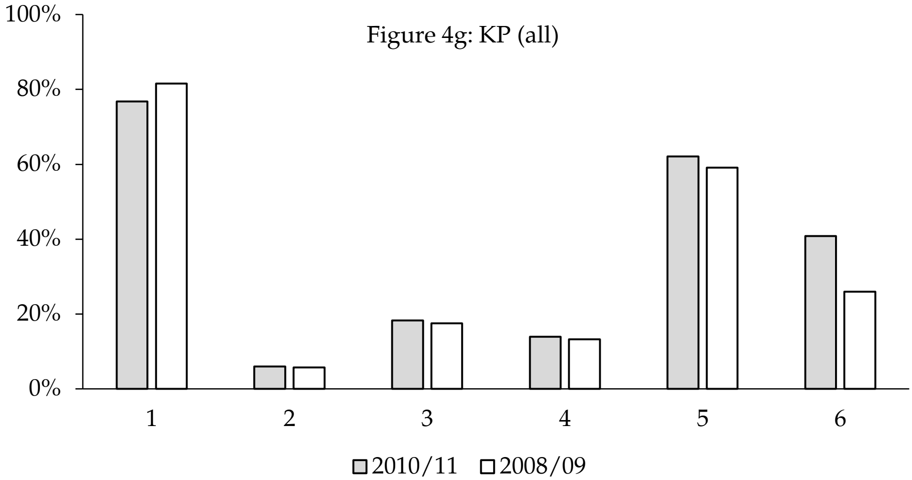


Figure 4g: KP (all)

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

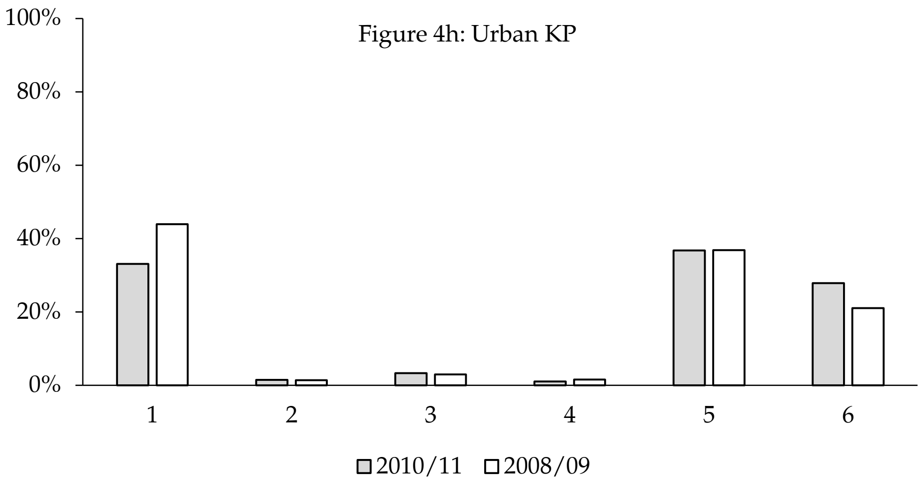
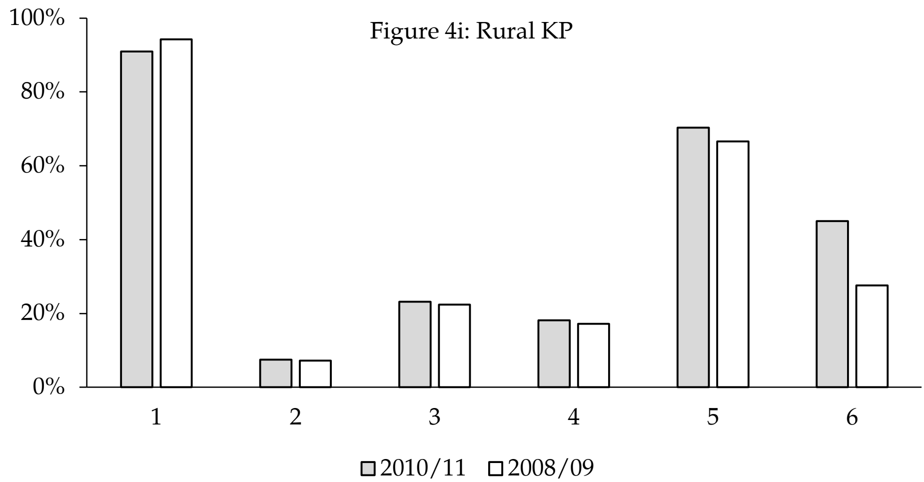
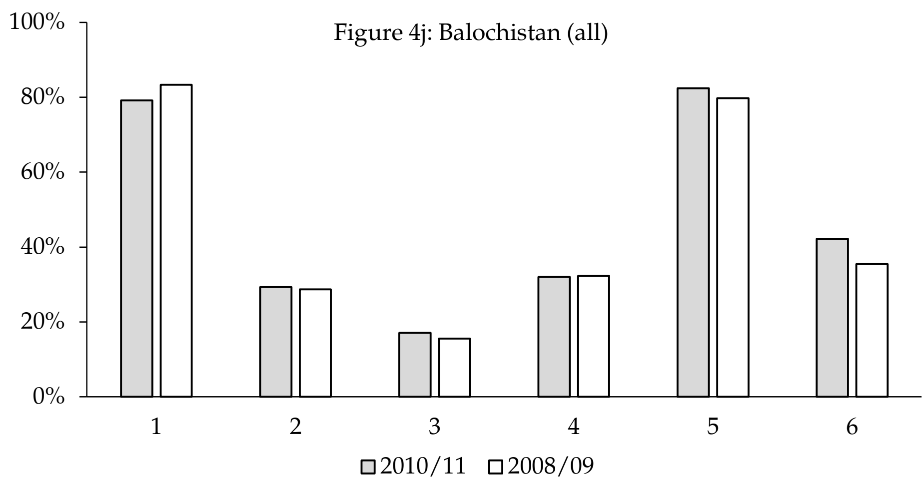


Figure 4h: Urban KP

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.



Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

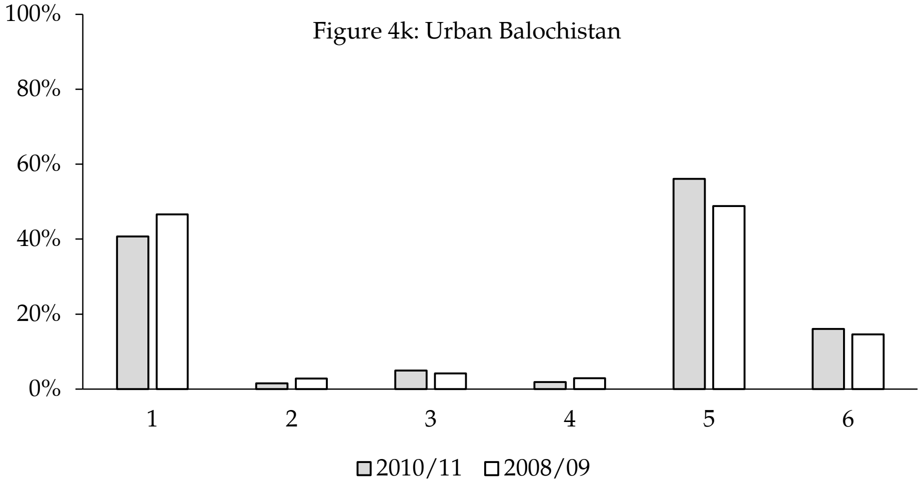


Figure 4k: Urban Balochistan

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.

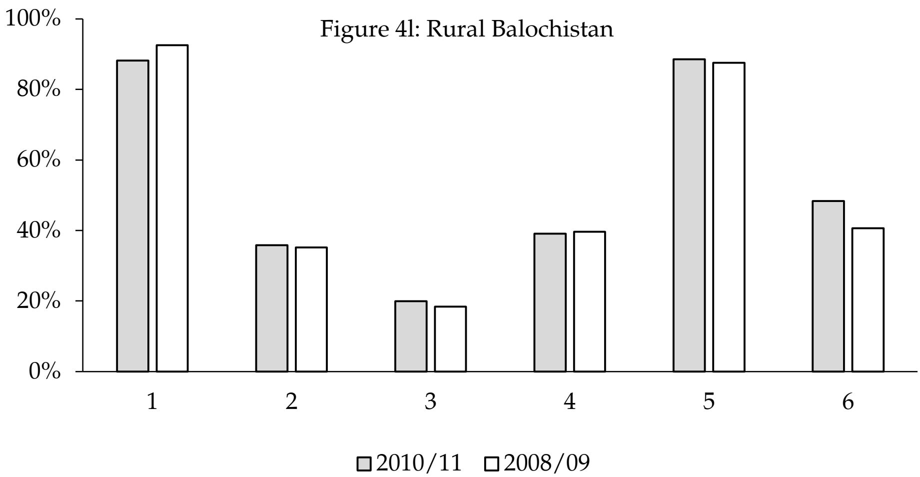


Figure 4l: Rural Balochistan

Note: 1 = cooking, 2 = lighting, 3 = mobility, 4 = space temperature regulation, 5 = refrigerator, 6 = TV/radio.
Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

The lack of modern cooking fuels accounts for the largest share of energy poverty at the household level: around 67 percent of households in Pakistan report using traditional fuels to cook. The use of modern fuels in rural areas is very low, with 91 percent of households relying on traditional fuels in rural KP. The use of energy for lighting yields a better picture: the percentage of deprived households remains in single digits except for rural Sindh and Balochistan where it is 17 and 36 percent, respectively.

Although the percentage of households that own an electric fan is closely related to the proportion using electricity as their main source of lighting, we observe a different trend in rural areas: many households that own an electric fan report using gas or kerosene as their main source of lighting instead. This could be explained by the relative cost factor, where households restrict their use of electricity to meeting only those energy needs that cannot be met otherwise.[8]

The mobility dimension of the MEPI is more prominent in rural areas, particularly in rural KP and Balochistan. With respect to the services and entertainment dimension, our findings show that around 64 percent of households do not own a refrigerator while 36 percent lack a TV/radio, reflecting lower use of electricity.

4.4. *Comparison of MEPI, 2008/09 and 2010/11*

Figures 1–4 suggest that, on average, energy use has improved slightly at the national level between 2008/09 and 2010/11. Although the overall MEPI and proportion of energy-poor households (H) has declined across rural Pakistan, the intensity of deprivation (A) for these households has risen slightly over this period. Thus, it has become more difficult for energy-poor households to meet their energy needs over time.

The level of energy deprivation in terms of cooking fuels has a small downward trend across Pakistan from 2008/09 to 2010/11. Overall, rural areas reflect greater deterioration in terms of energy use (barring rural Sindh), but even urban Balochistan has fared badly. This poorer performance over time also emerges across the services dimension, while households in rural Punjab and in both urban and rural Balochistan face higher levels of deprivation in terms of energy for mobility. Finally, rural KP and Balochistan have both witnessed a fall in access to electricity for lighting, so that most rural households tend to rely on other sources to meet their lighting needs.

5. Conclusion

Given the upward trend in energy poverty in Pakistan, this study analyzes the provision of energy at the household level, using a comprehensive, country-specific index adapted from Nussbaumer et al.

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[8] The problem of energy poverty tends to be aggravated by income poverty. We find that the lower income quintiles account for a higher percentage of energy-poor households. However, even the highest income quintile features energy poverty, which highlights the difference between the two concepts.

(2012). We focus on deprivation rather than access to energy in estimating energy poverty at the national and provincial levels for 2010/11 and 2008/09. The energy poverty index we have adapted measures five dimensions of energy that are deemed essential to a baseline standard of living. These include cooking, lighting, mobility, space temperature regulation and services provided by energy.

The study finds that energy poverty fell slightly between 2008/09 and 2010/11, with the MEPI declining slightly to 0.265 from 0.267. Our findings show that rural areas tend to face higher levels of energy deprivation than urban areas. It is worth mentioning that our calculations do not take into account scheduled power outages, which affect the use of electricity-powered amenities. This factor is likely to have produced underestimates of the MEPI for the country in general and for rural areas in particular, which were subject to long periods of electricity outages during both survey rounds.

Our results call for steps to improve the availability of energy in Pakistan, particularly the provision of modern cooking fuels and energy for lighting and transport. This implies that the government should ensure that projects designed to deliver electricity and related services are completed on time. Moreover, rural areas and the province of Balochistan, which face higher levels of deprivation, need special attention in this context. The China–Pakistan Economic Corridor project represents a significant opportunity in this respect, giving Pakistan the chance to initiate new energy projects in less developed areas of the country.

Future avenues of research include developing a richer set of representative indicators for each dimension and adding new dimensions depending on the data available. This would help refine measures of energy poverty for Pakistan and allow comparisons with other South Asian countries as well as the rest of the world.

References

Awan, R., Sher, F., & Abbas, A. (2013, December). *An investigation of multidimensional energy poverty in Pakistan*. Paper presented at the 29th AGM of the Pakistan Society of Development Economists, Islamabad.

Barnes, D. F., Khandker, S. R., & Samad, H. A. (2011). Energy poverty in rural Bangladesh. *Energy Policy*, *39*(2), 894–904.

Bravo, V., Mendoza, G. G., Legisa, J., Suárez, C. E., & Zyngierman, I. (1983). *A first approach to defining basic energy needs*. Tokyo: United Nations University.

Department for International Development. (2002). *Energy for the poor: Underpinning the Millennium Development Goals*. London: Author.

Fitzgerald, K. B., Barnes, D., & McGranahan, G. (1990). *Interfuel substitution and changes in the way households use energy: The case of cooking and lighting behavior in urban Java* (Industry and Energy Department Working Paper No. 29). Washington, DC: World Bank.

Foster, V., Tre, J.-P., & Wodon, Q. (2000). *Energy prices, energy efficiency and fuel poverty*. Unpublished manuscript, World Bank, Latin American and Caribbean Regional Studies Program, Washington, DC.

Goldemberg, J., & Johansson, T. B. (1995). Overview: Energy as an instrument for socioeconomic development. In T. B. Johansson & J. Goldemberg (Eds.), *Energy as an instrument for socioeconomic development* (pp. 9–17). New York: United Nations Development Programme.

Hu, Z., & Hu, Z. (2013). *Electricity economics: Production functions with electricity*. Berlin: Springer-Verlag.

International Atomic Energy Agency. (2005). *Energy indicators for sustainable development: Guidelines and methodologies*. Vienna: Author.

Leach, G., & Mearns, R. (1988). *Beyond the wood fuel crisis: People, land and trees in Africa*. London: Earthscan.

Mirza, B., & Szirmai, A. (2010). *Towards a new measurement of energy poverty: A cross-community analysis of rural Pakistan* (UNU-MERIT Working Paper No. 24). Maastricht: Maastricht Economic and Social Research and Training Centre on Innovation and Technology.

Munasinghe, M. (1992, June). *Environmental economics and sustainable development*. Paper presented at the UN Earth Summit, Rio de Janeiro.

Nussbaumer, P., Bazilian, M., & Modi, V. (2012). Measuring energy poverty: Focusing on what matters. *Renewable and Sustainable Energy Reviews*, *16*(1), 231–243.

Nussbaumer, P., Nerini, F. F., Onyeji, I., & Howells, M. (2013). Global insights based on the multidimensional energy poverty index (MEPI). *Sustainability*, *5*(5), 2060–2076.

Pachauri, S., Mueller, A., Kemmler, A., & Spreng, D. (2004). On measuring energy poverty in Indian households. *World Development*, *32*(12), 2083–2104.

Pachauri, S., & Spreng, D. (2004). Energy use and energy access in relation to poverty. *Economic and Political Weekly*, *39*(3), 271–278.

Sarin, M. (1991). Improved stoves, women and domestic energy. *Environment and Urbanization*, *3*(2), 51–56.

Schultz, T. P. (1990). *Returns to women's education* (Economic Growth Center Discussion Paper No. 603). New Haven, CT: Yale University Press.

Smith, K. R., Mehta, S., & Maeusezahl-Feuz, M. (2004). Indoor air pollution from household use of solid fuels. In M. Ezzati, A. D. Lopez, A. Rodgers & C. J. L. Murray (Eds.), *Comparative quantification of health risks: Global and regional burden of disease attributable to selected major risk factors* (chap. 18). Geneva: World Health Organization.

Sovacool, B. K., Cooper, C., Bazilion, M., Johnson, K., … Raza, H. A. (2012). What moves and works: Broadening the consideration of energy poverty. *Energy Policy*, *42*, 715–719.

United Nations Development Programme. (2000). *World energy assessment: Energy and the challenge of sustainability*. New York: Author.

United Nations Millennium Project. (2005). *Investing in development: A practical plan to achieve the Millennium Development Goals*. New York: UNDP.

van der Klaauw, B., & Wang, L. (2003). *Child mortality in rural India: Determinants and policy implications*. Unpublished manuscript, World Bank, Washington, DC.

World Bank. (2002). *ESMAP business plan, 2002–2004*. Washington, DC: Author.

World Commission on Environment and Development. (1987). *Our common future*. New York: Oxford University Press.

Appendix

Table A1: MEPI scores for Pakistan, by province and region

Country/province	Year	H	A	MEPI
Pakistan	2010/11	0.562	0.471	0.264
	2008/09	0.572	0.466	0.267
Pakistan (urban)	2010/11	0.190	0.368	0.070
	2008/09	0.223	0.369	0.082
Pakistan (rural)	2010/11	0.762	0.485	0.370
	2008/09	0.764	0.482	0.368
Punjab	2010/11	0.494	0.425	0.210
	2008/09	0.515	0.418	0.215
Punjab (urban)	2010/11	0.185	0.366	0.068
	2008/09	0.225	0.363	0.082
Punjab (rural)	2010/11	0.707	0.435	0.308
	2008/09	0.715	0.430	0.307
Sindh	2010/11	0.526	0.473	0.249
	2008/09	0.544	0.491	0.267
Sindh (urban)	2010/11	0.144	0.375	0.054
	2008/09	0.175	0.385	0.067
Sindh (rural)	2010/11	0.803	0.486	0.390
	2008/09	0.814	0.508	0.413
KP	2010/11	0.623	0.465	0.290
	2008/09	0.603	0.448	0.270
KP (urban)	2010/11	0.243	0.362	0.088
	2008/09	0.273	0.364	0.099
KP (rural)	2010/11	0.746	0.476	0.355
	2008/09	0.715	0.458	0.328
Balochistan	2010/11	0.738	0.559	0.413
	2008/09	0.743	0.545	0.405
Balochistan (urban)	2010/11	0.313	0.370	0.116
	2008/09	0.313	0.366	0.115
Balochistan (rural)	2010/11	0.839	0.576	0.483
	2008/09	0.851	0.561	0.478

Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

Table A2: Percentage of poor households, by energy poverty and province

Country / province	Year	1	2	3	4	5	6
Pakistan	2010/11	0.890	0.083	0.112	0.097	0.702	0.448
	2008/09	0.920	0.084	0.097	0.097	0.710	0.416
Urban	2010/11	0.590	0.108	0.108	0.122	0.639	0.316
	2008/09	0.616	0.136	0.148	0.143	0.646	0.266
Rural	2010/11	0.163	0.023	0.026	0.011	0.355	0.118
	2008/09	0.189	0.024	0.049	0.014	0.390	0.110
Punjab	2010/11	0.900	0.170	0.167	0.202	0.846	0.460
	2008/09	0.927	0.218	0.221	0.237	0.833	0.380
Urban	2010/11	0.768	0.060	0.183	0.140	0.621	0.408
	2008/09	0.816	0.057	0.175	0.133	0.591	0.259
Rural	2010/11	0.330	0.015	0.033	0.010	0.367	0.278
	2008/09	0.439	0.014	0.030	0.015	0.368	0.210
Sindh	2010/11	0.910	0.075	0.232	0.182	0.704	0.450
	2008/09	0.942	0.072	0.224	0.172	0.666	0.276
Urban	2010/11	0.791	0.293	0.171	0.320	0.824	0.422
	2008/09	0.833	0.287	0.155	0.323	0.798	0.354
Rural	2010/11	0.407	0.015	0.049	0.018	0.561	0.160
	2008/09	0.466	0.028	0.042	0.029	0.488	0.146
KP	2010/11	0.882	0.358	0.200	0.391	0.886	0.484
	2008/09	0.925	0.352	0.184	0.397	0.875	0.406
Urban	2010/11	0.890	0.083	0.112	0.097	0.702	0.448
	2008/09	0.920	0.084	0.097	0.097	0.710	0.416
Rural	2010/11	0.590	0.108	0.108	0.122	0.639	0.316
	2008/09	0.616	0.136	0.148	0.143	0.646	0.266
Balochistan	2010/11	0.163	0.023	0.026	0.011	0.355	0.118
	2008/09	0.189	0.024	0.049	0.014	0.390	0.110
Urban	2010/11	0.900	0.170	0.167	0.202	0.846	0.460
	2008/09	0.927	0.218	0.221	0.237	0.833	0.380
Rural	2010/11	0.768	0.060	0.183	0.140	0.621	0.408
	2008/09	0.816	0.057	0.175	0.133	0.591	0.259

Source: Authors' calculations based on data from the PSLM for 2008/09 and 2010/11.

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