One way bets on pegged exchange rates

Ila Patnaik Ajay Shah^{*}

September 29, 2008

Abstract

Economic agents sometimes have homogeneous expectations about future fluctuations of a pegged exchange rate. When agents perceive a one way bet, this is likely to be expressed in the currency exposure of firms. In this paper we examine the direction of the currency exposure of firms in India over the period 1993-2008. We find that in the period the rupee was tightly pegged to the US dollar, and when large reserves were built up, a substantial set of firms had a statistically significant currency exposure where they gained from appreciation. In the fourth period that we examine, 93 of the 126 industry indexes show a currency exposure which would profit from appreciation.

^{*}This work was done under the NIPFP-DEA Research Program on Capital Flows and their Consequences. We are grateful to CMIE for all the databases used in the paper. The authors would like to thank the participants of the NIPFP-DEA research meeting, especially the discussant, Michael Hutchison, for comments.

Contents

1	Inti	roduction	3
2	Dat	a and setting	6
	2.1	Exchange rate regime	6
	2.2	Industry indexes	8
3	Me	asurement of currency exposure	8
	3.1	Measurement using accounting data	8
	3.2	Measurement using the stock market	9
	3.3	Trade weighted or bilateral exchange rate?	10
	3.4	Currency market returns or innovations?	10
	3.5	Lags in the response of stock prices	11
	3.6	Market portfolio in the regression	12
	3.7	Difficulties of statistical precision	13
	3.8	Changing exchange rate exposure across sub-periods	15
	3.9	Summary of estimation strategy	15
4	Res	sults	16
	4.1	Exchange rate exposure in the overall market index	16
	4.2	Exchange rate exposure for 11 broad industry indexes	17
	4.3	Methodological aspects of currency exposure	19
	4.4	Exchange rate exposure for fine grained industry indexes	21
5	Sen	sitivity analysis	22
	5.1	Choice of market index	22
	5.2	Choice of return interval	22
	5.3	Alternative definitions of periods	23
6	Cor	nclusion	23

1 Introduction

In this paper we examine unhedged exchange rate exposure under a pegged exchange rate regime. The empirical literature on exchange rate exposure of firms has broadly found a lack of unhedged currency exposure, especially with firms in the US.

In a floating exchange rate regime, forecasting future currency movements is difficult. In this paper, we focus on the *de facto* pegged exchange rates which are particularly prevalent in emerging markets. Pegged exchange rates can sometimes involve opportunities for profitable forecasting of future exchange rate movements. When a central bank is implementing a pent-up adjustment over an extended period of time, this creates expectations of currency movements in one direction. Alternatively, if a central bank is doing sustained trading on the currency market, month after month, then the private sector could believe that the exchange rate has been distorted. When there are inconsistencies in the monetary policy framework, the private sector can form a view that such one-sided trading by the central bank is not sustainable. This can be used for forecasting future movements of the currency. When large reserves are built up, the private sector can rule out the scenario of a large depreciation taking place.

When a large number of private players have a consensus on the future direction of currency movements, this constitutes a one-way bet on the exchange rate. When managers of firms have such beliefs about future exchange rate fluctuations, they are likely to modify the exposures of firms so as to profit from anticipated exchange rate fluctuations.

Much of the empirical literature on exchange rate exposure measures exposure using stock price data and examines the impact of a change in the exchange rate on the value of firms. The evidence on currency exposure is mixed. Few find strong evidence of significant currency exposure. For example, Dominguez and Tesar (2006a) find that in 5 out of the 8 countries studied only about 20 percent of firms are exposed. Only in 3 countries, 40 percent of industries are exposed. Much of the literature examines data from countries that have floating exchange rates. These empirical results, which find little currency exposure, could partly reflect the fact that with floating exchange rates, forecasting future exchange rate changes is difficult. In addition, since the currency is more volatile firms have an incentive to hedge (Bartram, 2007). When it comes to industry indexes, negative and positive currency exposures of firms tend to cancel out when firms hold different views about currency movements (Allayannis and Ihrig, 2000; Dahlquist and

Robertsson, 2001; Griffin and Stulz, 2001). This would yield low exposures when measurement is done using industry indexes.

In the context of pegged exchange rates, Parsley and Popper (2006) examine the issue of exchange rate pegs and currency exposure of firms in East and South East Asia and find significant foreign currency exposure. They find that firms are less hedged under pegged exchange rates. Their evidence on the direction of exposure is, however, mixed. They do not find that firms make one way bets on the exchange rate and are short dollars when the local currency is expected to appreciate. Similarly, Patnaik and Shah (2007) finds that Indian firms have a larger currency exposure when exchange rate flexibility is lower.

The lack of evidence of currency exposure may reflect difficulties in measurement. Most empirical studies such as Adler and Dumas (1984); Jorion (1990); Doukas *et al.* (2003); Priestley and Odegaard (2007) use stock prices to measure currency exposure of firms. We draw on this work, identify sources of difficulty in measurement, and address them in our estimation strategy.

India is an interesting laboratory for several reasons. India has a well functioning and liquid equity market, which yields stock market data for thousands of firms with active trading. India has a pegged rupee-dollar exchange rate regime, but has been through four sub-periods with different characteristics of the pegged exchange rate. In recent years, there has been sustained one-way pressure on the exchange rate, with large scale purchases by the central bank aiming to prevent rupee appreciation.

Under these conditions of exchange rate pegging with a large reserves buildup, economic agents could feel that large depreciations are ruled out, and future appreciation is likely. Hence, many firms would be expected to hold currency exposure so as to profit from appreciation. The main hypothesis of this paper is that in the recent years, when there was sustained one-way currency intervention by the central bank and massive reserves were built up, many firms exploited this one way bet.

A key aspect of this hypothesis is a homogeneity of expectations across many firms. There would be lesser cancelling out of positive and negative exposures between the firms in an index, thus revealing exchange rate exposure in an industry index or an overall market index.

Under this hypothesis, the exposures of firms and industries would not simply mirror net exports. The efforts of managers to profit from anticipated currency movements would outweigh the exposure caused by net exports. In some cases, we would see some exporters standing to gain from an appreciation.

We show that in measuring the currency exposure of a *firm*, statistical precision is hard to obtain in an emerging markets setting with a pegged exchange rate. Hence, we shift focus from individual firms to industry indexes, where greater precision can be obtained. In the literature, currency exposure with industry indexes has often not been discernable, owing to the cancelling out of positive and negative exposures across firms in the industry. However, since the phenomenon of interest lies in the one-way bets in a pegged exchange rate, we hypothesise that firms can have homogeneous views and unhedged exposures, and that strong exposures would be visible at the level of industry indexes.

The results show that for some periods the Indian pegged exchange regime has been a one-way bet in the eyes of a large fraction of firms. In the fourth period that we examine, 93 of the 126 industry indexes show a currency exposure which would profit from appreciation.

The dataset used in this analysis reflects the currency exposure of large firms with stock market listings. Small and medium sized firms who do not have access to stock markets are not part of the study. To the extent that some industries such as garments or leather have a significant section of exports originating from such enterprises, the analysis is only a partial analysis of exchange rate exposure of firms in India at large.

This paper contributes to the literature on exchange rate exposure. It focuses on exchange rate exposure as a rational response of firms to the exchange rate regime. It adds to the empirical literature by examining the currency exposure of exporting industries within the context of a pegged exchange rate. It improves on existing methodologies for the measurement of exposure.

The remainder of this paper is organised as follows. In Section 2 we identify different phases in India's pegged currency regime and discuss the firm level data set. Section 3 discusses measurement of currency exposure of firms and describes the methodology adopted in this paper. Section 4 discusses our results. Section 6 concludes.

2 Data and setting

2.1 Exchange rate regime

While the Indian rupee has been a *de facto* peg to the US dollar since it became a 'market-determined exchange rate' in 1993, there have been periods when there has been considerable pressure on the rupee to appreciate. In these periods, the rupee was slowly permitted to appreciate, while the central bank purchased dollars on a considerable scale (Patnaik, 2007).

Exchange rate pegging can lead to distorted exchange rates. When a central bank buys on a massive scale on the currency market, month after month, economic agents are likely to believe that the exchange rate is undervalued. When reserves become very large, large depreciations become unlikely. If the monetary policy framework is perceived to be inconsistent, economic agents expect that the pattern of continual intervention is unsustainable (Patnaik, 2005). Alternatively, a managed exchange rate can be on a trajectory where a large adjustment of the exchange rate is being spread over an extended period through trading by the central bank. In these scenarios, a 'one way bet' can arise, where a large fraction of firms agree on the predicted direction of the exchange rate.

While India has broadly had a pegged exchange rate regime, there has been substantial structural change in the exchange rate regime. We identify break dates in the exchange rate regime using Zeileis *et al.* (2008). We use daily data on exchange rates for the INR, GBP, EUR and JPY from the Federal Reserve Bank of New York for implementing this methodology. This gives us four subperiods in India's exchange rate regime:

- 1. April 1993 February 1995: Low flexibility, appreciation prevented by reserves accumulation
- 2. February 1995 August 1998: High flexibility, Asian crisis, fears of depreciation
- 3. September 1998 March 2004: Low flexibility, appreciation prevented by reserves accumulation
- 4. March 2004 February 2008: Higher flexibility, massive reserves accumulation.

Table 1 shows the variation of currency volatility of the INR/USD exchange rate across these four periods. It rose from 0.16% per week in Period 1 to a

Table 1 Currency volatility and reserves build-up INR/USD Reserves addition (Bln. USD) Dates Weekly vol Overall Per vear						
			INR/USD	Reserves a	addition (Bln. USD)	
		Dates	Weekly vol.	Overall	Per year	
	1	1993-04 - 1995-02	0.16	13.03	6.93	
	2	1995-02 - 1998-08	0.93	4.86	1.39	
	3	1998-08 - 2004-03	0.29	82.64	14.81	
	_4	2004-03 - 2008-02	0.63	178.23	46.40	

Figure 1 Foreign currency purchases by RBI, and reserves

The vertical lines demarcate the four periods based on structural breaks in the currency regime.



nearly six-times higher level of 0.93% per week in Period 2. In Period 3 it dropped to one-third (to 0.29) and then roughly doubled (to 0.61) in period 4.

The dates of structural break identified above have interesting economic interpretations when juxtaposed against the foreign currency reserves and purchases of the Reserve Bank of India (RBI). Figure 1 shows the monthly timeseries of foreign currency reserves and of net purchase of foreign exchange by RBI. The three vertical lines demarcate the four periods that we examine.

For Period 1, the rupee had just shifted into the new 'market determined exchange rate'. Data for net purchase has not been released, and there was a small buildup of reserves. India had experienced a currency crisis in 1991, and there were concerns about future difficulties. Within Period 2, the period of the Asian crisis, a small decline in reserves took place and currency flexibility rose sharply. In Period 3, there was sustained currency intervention almost entirely on one side of the market, and reserves rose dramatically. This may have been a period when economic agents felt that the currency was likely to appreciate. Finally, in Period 4, while intervention data shows a less sustained pattern, the presence of large reserves would suggest to economic agents that a big depreciation was unlikely.

As is visible in Table 1, the characteristics of the four periods can be summarised in two dimensions. In Periods 1 and 3, currency volatility was low. In Periods 3 and 4, the pace of reserves accretion was high.

2.2 Industry indexes

The Centre for Monitoring Indian Economy (CMIE) maintains a family of industry indexes. At the uppermost level are 11 broad industry groups. These are then further sub-divided into finer industry categories in a tree structure. Totally, there are 164 industry indexes. Daily data is released for these indexes from July 1990 onwards. For some industries, in the early years, there were too few firms in an industry to permit meaningful computation of an industry index. In these cases, the time-series for the industry index is shorter.

We focus on two groups of indexes. For illustrative calculations, we use the 11 top level (broadest) industries. For the main results, we go down to the leaf nodes in order to have the finest possible industry classification. This procedure ensures that the natural economic exposure of all firms, through international trade on either inputs or finished goods, in one industry index is relatively homogeneous. There are 126 such fine-grained industry indexes. We measure currency exposure for this group of 126 industries.

3 Measurement of currency exposure

3.1 Measurement using accounting data

Many researchers have measured the currency exposure of firms through accounting disclosures (Kamil, 2006; Cowan *et al.*, 2004; Martinez and Werner, 2002). However, this strategy of is of limited usefulness for a variety of reasons, especially in India. Disclosures required to compute the currency risk associated with foreign currency borrowing, and the currency derivatives position of the firm, are not available in India. Further, deeper issues of currency exposure that arise through import parity pricing of raw materials and/or finished goods are outside the scope of accounting disclosure. In the accounting data, firms disclose direct imports and exports. However, if a firm sells to a trading company which (in turn) exports, this is not observed. The invoicing currency of transactions is not disclosed.

The currency exposure of financial firms is particularly important in thinking about financial fragility in the context of pegged exchange rates. Burnside *et al.* (2001) argue that in a world with government guarantees it is optimal for banks to have an unhedged currency mismatch between their assets and their liabilities. At the same time, it is difficult to estimate exposure from accounting disclosures for opaque financial firms such as banks.

For these reasons, the analysis of accounting disclosures yields a incomplete understanding of the currency exposure of the firm.

3.2 Measurement using the stock market

The currency risk visible in the stock price process is an attractive alternative mechanism through which currency exposure can be measured. An 'augmented market model':

$$r_i = \alpha + \beta_1 r_{M1} + \beta_2 r_{M2} + \epsilon \tag{1}$$

relates firm returns r_j to market index movements r_{M1} and currency fluctuations r_{M2} . The coefficient β_2 measures the sensitivity of the firm valuation to changes in the exchange rate. If an exporting firm is unhedged and gains when there is a currency depreciation, it would have $\beta_2 > 0$. This approach for measuring exposure of firms has been the workhorse of empirical papers which have explored currency risk using firm level data (Dominguez and Tesar, 2006a).

In an efficient market, this has the advantage of reflecting the efforts of speculative markets at putting together all aspects of currency exposure of the firm. This approach works identically for financial firms as it does for non-financial firms. If a firm sells a product which is priced through import parity, stock market speculators who form a judgment about future profits of the firm will embed currency fluctuations into the stock price process. Stock market speculators have an incentive to unearth information about the currency derivatives position of the firm and the invoicing currency of international trade of the firm.

While Equation 1 is an attractive approach for the measurement of currency exposure of firms, there are many hurdles faced in translating this idea into a

concrete estimation strategy. We hence turn to a discussion of the difficulties faced, and the strategy that we adopt in addressing these difficulties.

3.3 Trade weighted or bilateral exchange rate?

Much of the literature that studies firm currency exposure focuses on exposure to the trade weighted exchange rate (Bodnar and Wong, 2003; Dominguez and Tesar, 2006a). Some studies, such as Doukas et al. (2003), analyse the impact of both bilateral and trade weighted exchange rates and find that the results for both show that Japanese firms are sensitive to exchange rate changes. Dahlquist and Robertsson (2001) use three bilateral rates and a competitiveness weighted index for measuring currency exposure of Swedish firms. Dominguez and Tesar (2006b) use industry specific exchange rates for firms within an industry. We choose to focus on a bilateral exchange rate - the rupee-dollar exchange rate. This is because more than 80 percent of India's trade is denominated in the US dollar. In addition, the exchange rate regime is a *de facto* pegged rupee-dollar rate. The dollar is thus the relevent currency for questions relating to the relationship between the currency regime and firm exposure. Further, the use of trade weighted exchange rate, which is available at a monthly frequency, restricts the analysis. Stock prices react much more quickly to changes in the exchange rate.

3.4 Currency market returns or innovations?

In a competitive market, exchange rate changes are unpredictable, but this need not be the case when there is pegging. The stock price of a firm at any point of time takes into account all information available at that point. If a change in the exchange rate is expected in time t + 1, the stock price at time t takes this into account. Thus, the stock market price responds only to unanticipated changes in the exchange rate. Many studies in the literature follow Jorion (1990) and use the level of stock prices. In this paper, we follow Doukas *et al.* (2003) in using innovations or unexpected changes to stock market prices. We measure the response of the stock market to innovations in the currency returns time-series. We find that the time-series of the INR/USD exchange rate often deviates from a random walk. To get an accurate estimate of the innovations to the currency our ARMA identification is based on the Akaike Information Criterion which suggests that r_{M2} often has an AR time-series structure. Hence, we shift from raw currency market returns r_{M2} to ARMA innovations, that we call e_t .

3.5 Lags in the response of stock prices

Exchange rate fluctuations usually do not find their way into the stock price on the same day. It could take some time for stock market speculators to understand their implications. Further, this delay in information flow will differ across stocks based on their liquidity.

The issue of the lagged response of stock prices to currency movement is addressed by nearly every study on this issue. Several studies find that currency exposure increases when a longer return horizon is used. So while daily and weekly data does not show currency exposure, when the return horizon is monthly, the results suggest exposure (Bodnar and Wong, 2003; Chow and Chen, 1998; Dominguez and Tesar, 2006b). Their results suggest that analysis based on a shorter time horizon underestimates currency exposure.

Preliminary analysis suggested that stock prices in our dataset responded not only to weekly changes in the exchange rate, but also daily changes. However, the response often did come with a lag. When there are lags in the impact of exchange rate innovations upon the stock price, and if a researcher uses a fixed k = 1, this would lead to a bias in favour of obtaining exposures which are closer to zero. Hence, we enlarge the model to link the present stock market returns to present and past currency market innovations:

$$r_{jt} = \alpha + \beta_1 r_{M1,t} + \sum_{i=0}^k a_i e_{t-i} + \epsilon_t$$

$$\tag{2}$$

Under this specification, an innovation e_t on the currency market has an impact on the stock price at time t and the following k time periods. In equation 2, currency exposure is embedded in the vector of a_i coefficients; it is no longer a simple scalar β_2 as was the case under the model 1.

We identify the k that yields the best value of the Schwartz Bayesian Criterion for each r_j series separately. This allows the lag structure to vary based on stock market liquidity.

Since the exchange rate series has been re-expressed as a series of innovations, the total impact of an unexpected change in the exchange rate on a stock price is the sum of β_2 coefficients across all lags. To address the problem of heteroscedasticity in r_{M1} and r_{M2} we use a HAC estimator of the covariance matrix.¹

¹This is implemented using the methods of Zeileis (2004).

3.6 Market portfolio in the regression

The market index, r_{M1} , that plays an important role in the estimation of the market model, reflects the average stock market returns of firms in the market index. If one-way bets *are* present on the currency, and a large number of firms have a certain direction of exposure, this will result in currency exposure of the market index.

Under these conditions, when the estimated $\beta_2 = 0$, this means that the stock has the same exposure as the market index. The exposure measured by β_2 is not the currency exposure of the firm: it is the exposure of a particular firm over and above the exposure of the market index or the average firm.

Some studies (Bodnar and Wong, 2003; Dominguez and Tesar, 2001) suggest utilisation of an equally weighted market portfolio, rather than the more conventional value weighted market portfolio, as a consequence of this problem. They argue that a value weighted index gives greater importance to larger firms which are more internationalised and likely to have more currency exposure. In contrast, an equal weighted index gives greater importance to small firms who may produce more non-traded goods and have less exposure, thus diminishing the currency exposure of the market index.

The alternative strategy consists of orthogonalising the market index timeseries by first estimating a regression model explaining r_{M1} as a function of past and present currency innovations, and extracting the residual from this regression (Griffin and Stulz, 2001). Priestley and Odegaard (2007) go further, orthogonalising the market index return with respect to a number of macroeconomic variables which also affect the exchange rate. However, this requires macroeconomic time-series that are observed at a high frequency.

We follow the methodology of Griffin and Stulz (2001), which is better suited for use with high-frequency returns data. We set up a regression of r_{M1} on currency innovations with five days of lags, and extract residuals from this. These residuals represent pure equity index returns, uncontaminated by exchange rate effects (if any). These residuals are then used in the estimation of exchange rate exposure at the industry level.

If one-way bets were indeed present, and if the regression utilised r_{M1} as the explanatory variable, the estimated β_2 would reflect the *divergence* of the exposure of the firm from the exposure of the market index. This would, on average, be close to zero. This represents another source of a bias in favour of obtaining low currency exposures.



3.7 Difficulties of statistical precision

In the model

$$r_j = \alpha + \beta_1 r_{M1} + \beta_2 r_{M2} + \epsilon$$

high statistical efficiency in estimation of β_2 requires a high $\operatorname{Var}(r_{M2})$ and low $\operatorname{Var}(\epsilon)$. With pegged exchange rates, $\operatorname{Var}(r_{M2})$ is low. In emerging markets, $\operatorname{Var}(\epsilon)$ is high. Thus, an emerging markets setting with pegged exchange rates is one where statistical precision for estimation of β_2 is hard to obtain.

The numerical significance of this issue is judged through a Monte Carlo experiment where a true $\beta_2 = \frac{1}{2}$. Weekly data from 2003 to 2007 is simulated using the following assumptions. For an industrial country, currency volatility is set to the volatility of the GBP/USD exchange rate, while for the emerging market, the INR/USD volatility is employed. For the unsystematic risk in an emerging market, the value for one large Indian company (Satyam Computer Services) is used. For the industrial country, unsystematic risk is set to half this value.²

Figure 2 shows the distribution of β_2 obtained in this simulation. This suggests that if a firm had a true $\beta_2 = \frac{1}{2}$, this would be fairly accurately picked up

² This yields parameters a	for the simul	ation as follo	ws:
		Industrial	India
	$\operatorname{Var}(r_{M2})$	1.16	0.57
	$Var(\epsilon)$	1.86	3.72

in an industrial country setting, but there is substantial sampling variation in an emerging market setting.

One way in which this imprecision can be contained is by averaging β_2 across many firms. Even though each β_2 estimate has low efficiency, it is unbiased, and greater efficiency can be obtained by averaging across firms.

To do this, we shift focus from individual firms to industry indexes. All firms in an industry are likely to have similar characteristics in terms of imports, exports and the inherent currency exposure. If there is a one-way bet, and firms in an industry think alike, then this will materialise in significant values for β_2 for the industry index. If, on the other hand, firms have diverse views, then averaging to get to an industry index will involve averaging positive and negative values, thus giving industry β_2 values of near zero. Finding significant exposures for broad market indexes or industry indexes is, then, critically linked to the presence of one-way bets.

Exposure measured at the level of the industry (Bodnar and Gentry, 1993; Allayanis and Ihrig, 2000; Campa and Goldberg, 1995) may be an underestimate of the exposure of firms because positive and negative exposure may cancel out Dominguez and Tesar (2006b). In the literature, measurement of currency exposure at the level of industries has given even smaller estimates of exposure as compared with measurement of currency exposure at the level of firms. Allayannis and Ihrig (2000) find that 4 out of 18 US industries have significant exposure. Similarly, Dahlquist and Robertsson (2001) find that while Swedish *firms* carry significant exchange rate exposure, industry indexes do not. This could be related to the lack of a one-way bet under floating exchange rates, which would result in a diversity of currency views across firms, and a cancellation of positive and negative exposures within an industry.

Another perspective comes from Griffin and Stulz (2001) who examine the argument that some industries in a country complete with the same industries in other countries, and an appreciation of the exchange rate renders them less competitive. They find that the impact of exchange rate movements is trivial for most industries in Japan, US, Canada, France, Germany and UK. Industry shocks matter much more than exchange rate shocks. If the automobile sector in the rest of the world is doing badly, US firms are most likely to be negatively affected, than by the movement of the Yen/USD. They conclude that firms have many ways of hedging their exchange rate exposure, and even firms who export in international markets are able to efficiently organise themselves so that exchange rate changes have little effect on their valuation.

3.8 Changing exchange rate exposure across sub-periods

When using a dataset with a large span, estimating of exchange rate exposure is adversely affected by changing macroeconomic conditions. Expectations about future exchange rate fluctuations, and exchange rate volatility, could change through time. Firms are likely to attempt modifications of their exchange rate exposure at each time t in the light of their expectations about the risk and return at that time.

In order to address this problem, we utilise the methodology of Zeileis *et al.* (2008) to identify sub-periods in the exchange rate regime. The estimation strategy is then applied separately within each of these sub-periods.

3.9 Summary of estimation strategy

In summary, the estimation strategy followed in this paper consists of the following steps:

- 1. Work within dates of structural breaks of the exchange rate regime as identified by Zeileis *et al.* (2008).
- 2. Shift from r_{M2} series to innovations for each period separately, using an AR model.
- 3. Purge r_{M1} of currency effects and shift to residuals, using a lag structure chosen based on the SBC. This is also done separately in each of the four periods of the exchange rate regime, in order to reflect changing currency market conditions and views of firms.
- 4. Apply this strategy to a large database of industry indexes. We examine all industry groups, financial and non-financial.
- 5. Compute the augmented market model using orthogonalised equity index returns and currency innovations for each industry index, using the SBC to choose the lag structure.
- 6. The overall currency exposure of an industry is the sum of currency coefficients. Statistical significance is assessed using heteroscedasticity-consistent inference.
- 7. The model is estimated using daily data.

Table 2 Model explaining Nifty using present and lagged r_1					
		Period 1	Period 2	Period 3	Period 4
	Same day	0.538	-0.283	-1.204	-1.249
		(0.8)	(-2.4)	(-4.0)	(-8.1)
	Lag 1	1.060	-0.055	-0.603	-0.398
		(1.6)	(-0.5)	(-2.0)	(-2.6)
	Lag 2	0.877	0.092	0.002	-0.267
		(1.3)	(0.8)	(0.0)	(-1.7)
	Lag 3	-0.287	0.180	-0.342	0.173
		(-0.4)	(1.5)	(-1.1)	(1.1)
	Lag 4	0.656	0.124	0.431	-0.251
		(0.9)	(1.0)	(1.4)	(-1.6)
	Lag 5	1.008	-0.029	0.455	-0.119
		(1.6)	(-0.2)	(1.5)	(-0.8)
	\bar{R}^2	0.005	0.005	0.015	0.073

4 Results

4.1 Exchange rate exposure in the overall market index

As argued above, one key step of the estimation strategy is the task of purging the average currency exposure of firms that is embedded in the market index. If the exchange rate were not a one-way bet or if firms were constrained by capital controls and illiquid financial markets, there would be a dispersion of currency exposure at the firm level and these exposures would tend to cancel out, giving a market index with low or zero exposure.

Table 2 shows results for the four periods of India's exchange rate regime. In each time-period, an AR model is used to convert daily INR/USD percentage changes into a time-series of innovations. The regression shown in the table explains daily Nifty percentage changes using present and past currency market innovations.

Period 1 ran from April 1993 to February 1995. The INR had very little flexibility, capital controls were binding, and financial markets had little liquidity. In this period, the average firm had no exposure. The adjusted R^2 was 0.005, suggesting that currency fluctuations had very little impact on Nifty.

Period 2 ran from February 1995 till August 1998. There were fears of depreciation and the highest exchange rate flexibility in India's history. In this period, there was a small contemporaneous rise in Nifty of 0.283% for a 1% rupee appreciation. However, the adjusted R^2 was just 0.005, suggesting that currency fluctuations still did not matter for Nifty.

In period 3, there was low exchange rate flexibility, and reserves were built up at a high pace suggesting exchange rate undervaluation. Some appreciation of the rupee began. Towards the end of this period, difficulties of sterilisation were visible, which helped generate expectations of rupee appreciation. In this period, substantial coefficients are visible: a 1% rupee appreciation yields a 1.2% rise in Nifty on the same day and a 0.6% rise in Nifty on the next day adding up to a total benefit for Nifty of 1.8%. The adjusted R^2 rose to 0.015. Currency fluctuations thus started being relevant to Nifty in this period.

Finally, in period 4, which run from 3/2004 till 2/2008, there was greater exchange rate flexibility. But at the same time, there was a sustained intervention and massive reserves accumulation, which helped firms feel confident there was no risk of a substantial depreciation. In this period, a 1% rise in the rupee yields a 1.25% rise in Nifty on the same day and another 0.4% rise in Nifty on the next day adding up to a total benefit for Nifty of 1.65% (slightly smaller than that seen in Period 3). The adjusted R^2 rose substantially to 0.073. This suggests that by period 4, currency fluctuations were important in shaping Nifty.

In all four periods, the stock market processes information relatively rapidly: there are no lags beyond one day. This encourages us to utilise high frequency data so as to obtain statistical precision.

Our first key result is that in periods 3 and 4, when there was pressure on the rupee to appreciate, the average firm had setup a position so as to benefit from currency movements of some direction or the other.

Further, in terms of our estimation strategy, this procedure results in orthogonalisation of Nifty returns with respect to currency innovations.

4.2 Exchange rate exposure for 11 broad industry indexes

Table 3 shows the currency exposures of broad industry indexes. In period 1, there is heterogeneity of exposures. India had just moved away from an administered exchange rate following a currency crisis, overseas borrowing was limited and currency derivative markets were illiquid.

In period 2, a series of negative values are seen - i.e. firms that stand to gain

Table 3 Currency exposure of broad industry groups

This table shows the currency exposure of the 11 broad industry indexes defined by CMIE, in each of the four sub-periods. Values in brackets are t statistics. As an example, in the fourth period, a 1% INR/USD depreciation gave a 1.3462% decline in the Food and beverages index, with a t statistic of -7.89.

	P.1	P.2	P.3	P.4
Food and beverages	1.1613	-0.022	-0.8499	-1.3462
	(2.29)	(-0.21)	(-3.35)	(-7.89)
Textiles	0.702	-0.1006	-0.8832	-0.4695
	(1.06)	(-2.15)	(-2.87)	(-1.45)
Chemicals	1.6803	0.0519	-0.6813	-1.6609
	$(\ 3.3\)$	(0.3)	(-2.23)	(-12.95)
Non-metallic minerals	2.3461	-0.0146	-1.0844	-1.4509
	(4.57)	(-0.07)	(-3.96)	(-7.46)
Metals and metal products	3.8096	-0.4037	-2.6453	-2.308
	(3.28)	(-3.22)	(-5)	(-9.76)
Machinery	1.8535	-0.2224	-2.138	-3.2046
	(2.49)	(-3.83)	(-5.3)	(-3.42)
Transport equipment	4.2014	-0.2024	-1.7437	-1.7125
	$(\ 3.55\)$	(-3.88)	(-5.73)	(-13.15)
Electricity	4.5418	-0.1062	-0.7007	-1.7608
	(4.96)	(-0.74)	(-1.8)	(-8.57)
Non-fin services	-1.024	-0.1895	-1.9138	-1.1068
	(-1.07)	(-3.03)	(-4.37)	(-2.25)
Construction	0.8585	0.0357	-1.9572	-2.3282
	(1.36)	(0.18)	(-2.66)	(-2.59)
Finance	2.7802	-0.3202	-3.8574	-1.1467
	(2.54)	(-5.99)	(-2.64)	(-2.95)

Table 4 Net exports as a fraction of sales for 11 major industries							
	'89	'92	'95	'98	'01	'04	'07
Food & beverages		0.07	0.06	0.06	0.00	0.01	0.03
Textiles	-0.03	0.07	0.05	0.14	0.17	0.15	0.14
Chemicals	-0.08	-0.13	-0.13	-0.20	-0.15	-0.17	-0.22
Non-metallic mineral products	-0.07	-0.08	-0.06	-0.04	-0.02	0.00	-0.03
Machinery	-0.08	-0.05	-0.07	-0.07	-0.06	-0.05	-0.07
Transport equipment	-0.06	-0.01	-0.02	-0.03	-0.04	0.01	0.01
Electricity	-0.01	-0.21	-0.12	-0.03	-0.04	-0.03	-0.07
Construction	-0.01	0.03	0.02	0.05	0.05	0.06	0.05

from appreciation. Statistical significance at a 95% level is found with six of the 11 industries. The numerical values are, however, small.

In period 3, all industries show a negative exposure by sign, and all but one are significant at a 95% level of significance.

Finally, in period 4 also, all exposures are negative. In 10 out of 11 industries it is statistically significant. The textile industry is the only one where unhedged currency exposure is not statistically significant.

It is interesting to juxtapose these results about currency exposure against Table 4 which shows the net exports to sales ratio for eight of these industries. This juxtaposition shows that currency exposure is not driven by net exports. As an example, the food & beverages industry has been an exporter throughout. Yet, its exposure changed from a statistically significant coefficient of 1.16 in Period 1 (i.e. it would benefit from depreciation, as is typical of an exporter) to a statistically significant coefficient of -1.3462 in Period 4 (i.e. it would benefit from appreciation, which is not what is generally expected for an exporter).

Methodological aspects of currency exposure 4.3

Table 5 illustrates the methodological issues in estimating currency exposure. It focuses on the same 11 broad industry indexes that were used in Section 4.2. Panel I shows the results of estimating exchange rate exposure by utilising weekly data for the entire period. Here, none of the 11 industries show statistically significant currency exposure.

Panel II breaks down this same dataset by the four sub-periods of the exchange rate regime. Here, there are two industries which stand to gain from depreciation in Period 1. Apart from this, in the other three periods, there

As an illustration of the role of estimation strategy in identifying exchange rate exposure, we show calculations for the 11 broad (two digit) industry indexes defined by CMIE. Panel I shows the results of estimating simple augmented market models using weekly data. For none of the 11 industry indexes is the currency exposure statistically significant. Panel II introduces structural breaks. Panel III introduces purging of the currency exposure in r_{M1} . Panel IV introduces shifting the currency time-series into innovations. Finally, Panel V shifts to using daily data. These four methodological changes yield substantial effectiveness in isolating currency exposure.

	Number of industry indexes				
Methodology	Period 1	Period 2	Period 3	Period 4	
I. Weekly data, no structural					
breaks					
$t \leq -1.96$		(C		
$-1.96 < t \le 1.96$		1	1		
1.96 < t		(C		
II. Weekly data, structural					
breaks					
$t \leq -1.96$	0	0	0	0	
$-1.96 < t \le 1.96$	9	11	11	11	
1.96 < t	2	0	0	0	
III. Weekly data, structural					
breaks, purge r_{M1}					
$t \leq -1.96$	0	1	7	4	
$-1.96 < t \le 1.96$	8	10	4	7	
1.96 < t	3	0	0	0	
IV. Weekly data, structural					
breaks, purge r_{M1} , currency					
innovations					
$t \leq -1.96$	0	1	6	0	
$-1.96 < t \le 1.96$	8	10	5	11	
1.96 < t	3	0	0	0	
V. Daily data , structural					
breaks, purge r_{M1} , currency					
innovations					
$t \leq -1.96$	0	6	10	10	
$-1.96 < t \le 1.96$	3	5	1	1	
1.96 < t	8	0	0	0	

Table 6 Currency exposure for fine grained industry indexes

This table shows the number of fine grained industry indexes that fall into the three cases for statistically significant currency exposures, in each of the four sub-periods.

t statistic	Number of industry indexes					
of β_2	Period 1 Period 2 Period 3 Period 4					
$t \leq -1.96$	0	29	68	93		
$-1.96 < t \le 1.96$	91	94	57	33		
1.96 < t	32	1	0	0		

is no currency exposure.

Panel III introduces one more element of the methodology: purging the market index of the influence of the exchange rate. At this point, the broad contours of changing currency exposure are now visible. Panel IV introduces the purging of the currency returns time-series of autoregression. Finally, Panel IV switches to using daily data. At this point, substantial currency exposures, and changing currency exposures across sub-periods, are visible.

These calculations illustrate the importance of estimation strategy in identifying exchange rate exposure.

4.4 Exchange rate exposure for fine grained industry indexes

The main result of the paper is shown in Table 6. In the first period, there were 91 industry indexes with no significant currency exposure. There were 32 industry indexes which stood to gain from a rupee depreciation.

In the second period, there was 1 industry which stood to gain from a depreciation, and 29 industries stood to gain from an appreciation.

In the third and fourth periods, there was no industry index with a statistically significant positive exposure (i.e. that gained from depreciation). But a large number of industries stood to gain from appreciation: 68 industry indexes in Period 3 and 93 industries in Period 4. In Period 4, there were only 33 industry indexes where the null hypothesis of no exposure could not be rejected.

Table 7 Sensitivity analysis:	Switch to CM	IIE Cospi	as the ma	arket index
t statistic	Nu	umber of ind	lustry index	xes
of β_2	Period 1	Period 2	Period 3	Period 4
$t \leq -1.96$	0	29	70	98
$-1.96 < t \le 1.96$	93	94	55	28
1.96 < t	30	1	0	0

Table 8 Sensitivity analysis: Switch to weekly returns					
t statistic Number of industry indexes					
of β_2	Period 1	Period 2	Period 3	Period 4	
$t \leq -1.96$	0	7	17	89	
$-1.96 < t \le 1.96$	111	108	107	37	
1.96 < t	12	9	1	0	

5 Sensitivity analysis

In this section, we obtain evidence about the robustness of the main result (Table 6) across changes in estimation strategy.

5.1 Choice of market index

The results of Table 6 had utilised the Nifty index, which is made up of the top 50 large and liquid stocks of the country. Table 7 repeats the analysis using the CMIE Cospi index, which has roughly 2500 firms in the index. These results are stronger than those shown in Table 6: in Period 4, there are 98 industry indexes (instead of 93) which gain from rupee appreciation.

5.2 Choice of return interval

The results of Table 6 had utilised daily returns data. Table 8 repeats the analysis using weekly returns instead. In the first three periods, for many more industries, the null of no exposure cannot be rejected. This may be related to the reduction of statistical efficiency associated with time aggregation. As an example, Period 1 runs for 96 weeks and 671 days. However, Table 8 also has the basic character of the result of Table 6 where the number of industries which gain from rupee appreciation went up sharply through time. In Period 4, the number of industry indexes which stand to gain from appreciation (89) is much like the result obtained using daily data where 93 industry indexes have this direction of exposure.

Table 9 Sensitivity analysis: Sub-periods defined using structural breaks inmonths of import cover

t statistic	Number of industry indexes				
of β_2	Period 1	Period 2	Period 3	Period 4	
$t \le -1.96$	30	53	76	94	
$-1.96 < t \le 1.96$	95	71	49	32	
1.96 < t	0	0	0	0	

5.3 Alternative definitions of periods

The results of Table 6 had utilised sub-periods defined using the methodology of Zeileis *et al.* (2008), which focuses on structural change in an exchange rate regression. An alternative strategy consists of examining the time-series of import cover, defined as the number of months of imports that can be paid using foreign exchange reserves, for structural breaks. We identify dates of structural change in this using the ideas of Bai and Perron (2003) as implemented by Zeileis (2005). This analysis also shows four sub-periods with a different set of break dates: February 1999, February 2002, and April 2005.

Table 9 shows the results of our estimation strategy using these new definitions of the four periods. By these dates, in no sub-period was there a single industry index which stood to gain from depreciation. There was a considerable increase in the number of industry indexes which stood to have a statistically significant gain from appreciation.

6 Conclusion

There is an extensive literature on currency exposure of firms. However, since the analysis needs liquid stock markets for the augmented market model to be estimated, most of the empirical literature is located in countries with developed markets which largely have floating exchange rates. This paper contributes to the literature by examining currency exposure in a country with a pegged exchange rate. India is a good laboratory for such analysis because it has well developed stock markets, and a pegged exchange rate regime.

Estimation of currency exposure using stock prices is an area where considerable improvements have been obtained in the recent literature. This paper contributes to this literature by introducing some further improvements in this methodology.

The key result of this paper, and the question studied are, however, quite unique. We find that that firms seek to obtain profits from an expected movement of the exchange rate. While the currency exposure of industry indexes does reflect industry characteristics, this exposure varies a lot across time. In the fourth period, we find that 73% of industry indexes (93 out of 126) had a statistically significant bet on rupee appreciation. Such strong evidence of one way bets has not been found elsewhere in the literature. Similar work in other countries where exchange rate pegging has been combined with large reserves accumulation could possibly throw up interesting results.

References

- Adler M, Dumas B (1984). "Exposure to Currency Risk: Definition and Measurement." *Financial Management*, 13(2), 41–50.
- Allayanis G, Ihrig J (2000). "Effect of markups and on the exchange rate exposure of stock returns." *Technical report*, Board of Governors of the Federal Reserve System.
- Allayannis G, Ihrig J (2000). "The Effect Of Markups On The Exchange Rate Exposure Of Stock Returns." *Technical report*.
- Bai J, Perron P (2003). "Computation and Analysis of Multiple Structural Change Models." Journal of Applied Econometrics, 18, 1–22.
- Bartram S (2007). "What lies beneath: Foreign exchange rate exposure, hedging and cash flows." *Journal of Banking and Finance*.
- Bodnar G, Wong M (2003). "Estimating Exchange Rate Exposures: Issues in Model Structure." *Financial Management*, **32**(1), 35–67.
- Bodnar GM, Gentry WM (1993). "Exchange rate exposure and industry characteristics: evidence from Canada, Japan, and the USA." *Journal of International Money and Finance*, **12**(1), 29–45. Available at http://ideas.repec.org/a/eee/jimfin/v12y1993i1p29-45.html.
- Burnside A, Eichenbaum M, Rebelo S (2001). "Hedging and Financial Fragility in Fixed Exchange Rate Regimes." *European Economic Review*, 45, 1151–1193.
- Campa J, Goldberg L (1995). "Investment in manufacturing, exchange rates and external exposure." Journal of International Economics, **38**(3-4), 297–320.
- Chow EH, Chen HL (1998). "The determinants of foreign exchange rate exposure: Evidence on Japanese firms1." *Pacific-Basin Finance Journal*, **6**(1-2), 153–174. Available at http://ideas.repec.org/a/eee/pacfin/v6y1998i1-2p153-174.html.
- Cowan K, Hansen E, Herrera L (2004). "Currency Mismatches, Balance Sheet Effects and Hedging in Chilean Non-Financial Corporations." Eighth Annual Conference of the Central Bank of Chile, External Vulnerability and Policies for Prevention, Santiago, Chile.
- Dahlquist M, Robertsson G (2001). "Exchange rate exposure, risk premia, and firm characteristics." *Technical report*, Duke University, Durham, North Carolina.
- Dominguez K, Tesar L (2001). "A Reexamination of Exchange-Rate Exposure." The American Economic Review, 91(2), 396–399.

- Dominguez KM, Tesar LL (2006a). "Exchange rate exposure." Journal of International Economics, 68(1), 188–218.
- Dominguez KM, Tesar LL (2006b). "Exchange rate exposure." Journal of International Economics, **68**(1), 188–218. Available at http://ideas.repec.org/a/eee/inecon/v68y2006i1p188-218.html.
- Doukas JA, Hall PH, Lang LHP (2003). "Exchange Rate Exposure at the Firm and Industry Level." *Financial Markets Institutions and Instruments*, **12**(5), 291–346.
- Griffin J, Stulz R (2001). "International competition and exchange rate shocks: a cross-country industry analysis of stock returns." *Review of Financial Studies*, 14(1), 215–241.
- Jorion P (1990). "The Exchange-Rate Exposure of U.S. Multinationals." Journal of Business, **63**(3), 331–45. Available at http://ideas.repec.org/a/ucp/jnlbus/v63y1990i3p331-45.html.
- Kamil H (2006). "Does moving to a flexible exchange rate regime reduce currency mismatches in firms' balance sheets?" *Technical report*, IMF.
- Martinez L, Werner A (2002). "The Exchange Rate Regime and the Currency Composition of Corporate Debt: The Mexican Experience." Journal of Development Economics, 69(2), 315–34.
- Parsley D, Popper H (2006). "Exchange rate pegs and foreign exchange exposure in East and South East Asia." Journal of International Money and Finance, 25(6), 992–1009.
- Patnaik I (2005). "India's experience with a pegged exchange rate." In S Bery, B Bosworth, A Panagariya (eds.), "The India Policy Forum 2004," pp. 189-226. Brookings Institution Press and NCAER. URL http://openlib.org/home/ ila/PDFD0CS/Patnaik2004_implementation.pdf.
- Patnaik I (2007). "India's currency regime and its consequences." *Economic and Political Weekly.* URL http://openlib.org/home/ila/PDFD0CS/11182.pdf.
- Patnaik I, Shah A (2007). "Does the currency regime shape unhedged currency exposure?" *Technical report*, NIPFP.
- Priestley R, Odegaard BA (2007). "Linear and nonlinear exchange rate exposure." *Journal of International Money and Finance*, **26**(6), 1016–1037. Available at http://ideas.repec.org/a/eee/jimfin/v26y2007i6p1016-1037.html.

- Zeileis A (2004). "Econometric Computing with HC and HAC Covariance Matrix Estimators." *Journal of Statistical Software*, **11**(10), 1–17. URL http://www. jstatsoft.org/v11/i10/.
- Zeileis A (2005). "A Unified Approach to Structural Change Tests Based on ML Scores, F Statistics, and OLS Residuals." *Econometric Reviews*. Forthcoming, URL http://www.ci.tuwien.ac.at/~zeileis/papers/Zeileis-2005a.pdf.
- Zeileis A, Shah A, Patnaik I (2008). "Testing, Monitoring, and Dating Structural Changes in Maximum Likelihood Models." *Report 70*, Department of Statistics and Mathematics, Wirtschaftsuniversität Wien, Research Report Series. URL http://epub.wu-wien.ac.at/dyn/openURL?id=oai:epub.wu-wien.ac. at:epub-wu-01_dbc.