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Exchange rate regimes and FDI in developing countries:

a propensity score matching approach

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ABSTRACT

Theory suggests that regimes of relatively fixed exchange rates encourage inward foreign direct investment (FDI) relative to regimes of more flexible exchange rates. We use propensity score matching (PSM) to investigate the relationship between the exchange rate regimes of 70 developing countries and FDI into such countries using *de facto* regime classifications. We include a large number of variables in the logit equation that estimates the propensity score, the probability of regime choice. We also use general-to-specific modeling to get alternative, parsimonious versions. Based on four matching procedures, the average treatment effects suggest, with overall modest statistical significance, that relatively fixed *de facto* regimes do encourage FDI compared with relatively floating regimes. In addition, the estimated effects are sometimes economically large.

Keywords: Foreign direct investment, Exchange rate regime, Developing countries, Propensity score matching

JEL classification: C21; E5; F21; F33; O11

Highlights

- We investigate the impact of exchange rate regimes on FDI into developing countries.
- Propensity score matching is applied to a large set of developing countries.
- Both large and parsimonious logit models are used to generate the propensity scores.
- Average treatment effects suggest that *de facto* relatively fixed regimes encourage FDI.
- In addition, the estimated treatment effects are economically important.

1. Introduction

Economic theory suggests that fixed exchange rate regimes encourage more inward flows of foreign direct investment (FDI) than do floating exchange rate regimes (e.g., Aizenman, 1992). We investigate the possibility for a large set of developing countries using propensity score matching (PSM), a technique that has not previously been applied to the issue. Because of dissatisfaction (noted by, e.g., Tavlas et al., 2008) with the IMF's *de jure* regime classifications, which have been based on what countries tell the IMF their policy is, we use *de facto* regimes as defined by Reinhart and Rogoff (2004) (RR) and Levy-Yeyati and Sturzenegger (2005) (LYS). *De facto* regime classifications are based on observed behavior. In contrast to most economic models, the RR and LYS regime classifications are not just fixed and floating, but involve various degrees of fixedness relative to a pure float.

In accordance with theory, we find, for some regime comparisons, that relatively fixed regimes do lead to statistically significantly higher inflows of FDI than do more flexible regimes. The finding is more pronounced using the RR regime classifications. Overall, however, the statistical significance across all regime comparisons is probably best regarded as modest. Regarding economic importance, our point estimates have a wide range, sometimes indicating relatively large percentage increases in FDI under relatively fixed regimes, but sometimes not. Our results add to the meager past evidence on regime-choice and FDI for developing countries, supporting previous findings of Abbott et al. (2012).

Our approach, however, differs from that of Abbott et al. (2012) in several ways. First, PSM differs substantially from the regression approach of Abbott et al. (2012). In the analysis of the impact of a qualitative variable like exchange rate regime, PSM uses a completely different way of controlling for confounding variables, approximating a randomized controlled trial. And PSM does not rely on regression assumptions such as a linear relationship between dependent and independent variables or serially non-correlated errors. Our work also differs from Abbott et al. (2012) by adding several potentially important variables to the analysis and by employing a much longer estimation period.

The topic fits into the economics literature that examines the effects of exchange rate regime choice on a variety of macroeconomic variables such as economic growth, current account imbalances, price levels, and trade flows (see, *inter alia*, Frankel and Rose, 2002; Levy-Yeyati and Sturzenegger, 2003; Broda, 2006; Klein and Shambaugh, 2006; Bleaney and Francisco, 2007; Qureshi and Tsangarides, 2012; Gnimassoun, 2015; and Dorn and Egger, 2013, 2015). Gnimassoun (2015) emphasizes the importance of regime choice for developing countries, particularly in their quest for economic growth. He finds that flexible exchange rate regimes minimize external imbalances, and his implication is that this should encourage economic growth, although he writes that his results are not opposed to a choice of fixed exchange rates. In fact, there is a literature finding a beneficial effect of FDI on economic growth (e.g., Borensztein et al., 1998; Nair-Reichert and Weinhold, 2001; Li and Liu, 2005). Therefore, if our conclusion that relatively fixed regimes encourage FDI is correct, and if FDI encourages growth, then the negative impact of fixed rates on growth in developing countries reported by Levy-Yeyati and Sturzenegger (2003) and implied by Gnimassoun (2015) becomes less straightforward.[1]

Empirical exchange rate regimes consist of more than just the two possibilities of fixed and floating. Accordingly, LYS and RR have many more classifications that include various forms of fixing and relatively freely floating as well as many intermediate cases, such as crawling or frequently adjusted pegs, crawling bands, managed floats, and dirty floats. LYS have 8 classifications, which they place into the three broader classifications of fixed, intermediate, and floating. RR have 15 "fine" categories, which they reduce to 6 "coarse" categories. For our LYS analysis we use the fixed, intermediate, and floating categories. For our RR analysis we use the

[1] There is, however, no necessary contradiction. Suppose $growth = b_0 + b_1 FDI - b_2(fixed\ regime\ dummy) + other\ factors$, while $FDI = b_3 + b_4(fixed\ regime\ dummy) + other\ factors$, with all b parameters positive. Fixed regimes positively affect FDI but still negatively affect growth as long as $b_1 b_4 < b_2$.

coarse fixed category, an intermediate category that is the combination of the two coarse categories of crawling pegs or bands and managed floats, and the coarse category of freely falling. We omit the coarse freely floating and dual market categories, as they occur too infrequently for PSM to work credibly.[2] Despite the general dissatisfaction with them, we did try the IMF *de jure* regimes in preliminary work for the present paper, but, as in Abbott et al. (2012), there were no significant results. Therefore we omit the *de jure* categories from consideration in this paper.

2. Exchange rate regimes and FDI: theories, empirical findings, and motivation for PSM

The classic theoretical approach to exchange rate regimes and FDI starts by observing that exchange rate volatility may reduce FDI because of risk aversion, one of the possibilities in Cushman (1985), or through Dixit and Pindyck's (1994) option-value framework (Campa, 1993; Schiavo, 2007). Therefore, because fixed rate regimes have less volatility, a fixed rate regime would encourage inward FDI (Bénassy-Quéré et al., 2001; Krugman and Obstfeld, 2009). However, higher exchange rate volatility can alternatively increase FDI. One of the models in Cushman (1985) shows that a rise in export price accompanying reduced export supply from higher volatility can induce higher FDI and thus foreign production from multinational firms as a partial substitute for the reduced exports. Similarly, Goldberg and Kolstad (1995) show how FDI could be increased to reduce profit variance when exchange rate volatility rises and positive correlation exists between shocks to export demand and the price of foreign currency. Thus, the overall effect of the regime is ambiguous as far as risk aversion is concerned. Consistent with this ambiguity, empirical analyses with a variety of countries have found effects from volatility in both directions, or neither: significantly positive in Cushman (1985, 1988), Goldberg and Kolstad (1995), and Görg and Wakelin (2002); significantly negative in Campa (1993), Bénassy-Quéré et al. (2001), Chakrabarti and Scholnick (2002), De Vita

[2] After eliminating all observations with missing data for various variables, there are only 29 country/year occurrences of RR freely floating regimes. This is not enough for reliable PSM estimation. There are even fewer dual regimes. Also, adding the freely floating to the freely falling to get a larger floating group was unproductive, as it turned out to add virtually no additional usable data because of the PSM overlap condition and failures to find matches (discussed below).

and Abbott (2007), and Udomkerdmongkol et al. (2009); and insignificant in De Menil (1999) and Bouoiyour and Rey (2005).

Theoretical effects of exchange rate regimes on FDI that are independent of risk aversion have, however, been posited. In the case of developing countries, Bénassy-Quéré et al. (2001) note that, in addition to reducing volatility, a fixed (nominal) rate regime would lead to a gradually appreciating real home currency if the developing country is more inflationary than its FDI source countries. The resulting real host-country appreciation can discourage FDI inflows according to a number of theoretical treatments (Cushman, 1985, 1988; Froot and Stein, 1991; Blonigen, 1997). This would offset, and perhaps outweigh, the reduced-volatility effect. Schiavo (2007) proposes that reduced transactional and informational barriers from a currency union would encourage FDI. Finally, using a general equilibrium model in which investors are risk neutral, and in which an economy experiences real and nominal shocks, Aizenman (1992) finds that fixed rate regimes unambiguously encourage FDI relative to floating regimes. Abbott et al. (2012, pp. 97–98) give a succinct summary. Theoretical treatments don't explicitly deal with intermediate regimes. But if fixed rates encourage FDI relative to floating, then intermediate regimes, which tend to moderate exchange rate fluctuations, are also likely to be more encouraging to FDI than floating regimes, but less encouraging than fixed regimes.

Empirical work regarding the effect exchange rate regimes on FDI, as distinct from volatility, is scarce. For developed countries, Schiavo (2007) reports that the EMU currency union encouraged FDI among member countries as well as with other OECD countries. Abbott and De Vita (2011) extend the work by adding additional high-income countries and using *de facto* exchange rate regimes as defined by RR and by Shambaugh (2004). They support Schiavo's (2007) result that currency unions encourage FDI.

For developing countries, our focus, Abbott et al. (2012) examine LYS and RR *de facto* and IMF *de jure* regimes: fixed, intermediate, and floating. Abbott et al. (2012) conclude that RR and

LYS fixed and intermediate regimes promote inward FDI into developing countries compared with floating regimes. They find no significant effects from the IMF-defined *de jure* regimes. Busse et al. (2013) employ RR *de facto* regimes (only) and report no significant effect of fixed rate regimes on FDI into a large set of developing countries compared with non-fixed regimes. But they do report positive fixed-regime effects for developed countries.

Thus, the evidence on exchange rate regimes and FDI into developing countries is scarce and inconsistent. Moreover, it is exclusively based on regression approaches. While regression is, of course, widely used and of undoubted value, to confirm or not any of the existing results we argue for a completely different technique, propensity score matching, PSM. PSM employs a different way from regression of controlling for other variables in an analysis of the effect of a discrete treatment, here, exchange rate regime, on some outcome, here, FDI. We believe it useful to confirm, or not, existing results with results from different techniques. The PSM approach is also potentially important because the method relaxes the typical regression assumption of a linear relationship between FDI and its determinants (Black and Smith, 2004). If there are nonlinear relationships between any non-regime variables and FDI, and if such variables are also correlated with regime choice, then a regression which fails to account for the nonlinearity will be misspecified. PSM can address the problem. The problem is important because there do seem to be nonlinear relationships between FDI and its determinants (Carr, Markusen, and Maskus, 2001; Bergstrand and Egger, 2007; Blonigen and Piger, 2014). For example, there appear to be interaction effects involving variables like GDP and skilled labor endowment. We now provide a brief explanation of how PSM works, including how it can avoid the problem of nonlinearity in the regression approach.

3. An overview of PSM applied to exchange rate regimes and FDI

We wish to estimate how FDI into developing countries responds to various exchange rate regimes, while controlling for other factors. In a regression analysis, we would estimate an equation with FDI as the dependent variable and the exchange rate regime effect captured as the coefficient on a 0/1 dummy variable. Other factors would be controlled for by also including them in the equation, and some method might be employed to deal with possible endogeneity of right-hand variables. Regression is the approach of Abbott et al. (2012) and Busse et al. (2013).

In PSM analysis, one variable is the response variable (here, FDI), and another a 0/1 treatment variable (here, the exchange rate regime). One first estimates the probability, or "propensity score," that each individual in the data set would have been subjected to the treatment, controlling for other factors, often called "confounders" in the literature. The confounders, or covariates, may also include variables that influence FDI directly. The propensity score is usually computed with either probit or logit. We report results using logit, which seems to be the more popular choice (Deuss, 2012). Using probit made very little difference to the results of a number of cases where we tried it, consistent with the discussion in Caliendo and Kopeinig (2008).

The next step is to group together, or "match," individuals with very similar propensity scores for being treated. Within each group of matched individuals, one then observes that some actually did receive the treatment, and some did not (the controls). Propensity score matching approximates a randomized controlled trial in that the distributions of the confounders in the matched groups are (approximately) the same for the treated and controls (Austin, 2011). The procedures we follow provide additional checks that the distributions of each confounding variable can be assumed to be the same for the treated and controls in each group, which is the "balancing condition" (Rosenbaum and Rubin, 1983). Any difference in the mean outcome between the treated and the controls in each group is thus attributable to the treatment. Finally, one computes the mean difference in outcome between treated and controls across all the groups. The mean difference gives the estimate of the treatment effect, similar to the interpretation of the regression coefficient for an exchange rate dummy variable.

PSM can address the problem in regression analysis of unknown (and thus unspecified) nonlinear relationships between FDI and other variables. Because probabilities are bounded between

0 and 1, it is certain that any relationship between various variables and the probability of a regime is nonlinear as in, say, a logistic curve. Suppose some of these variables also affect FDI nonlinearly. If the regression specification omits the nonlinearity, then the included regime variable will be correlated with the omitted nonlinear terms, because the omitted terms will approximate to some extent the logistic curve. Thus, the regime coefficient in a regression will be biased. PSM, meanwhile, leads to computation of the regime coefficient by matching treated and control groups that have very similar confounder distributions. Thus any nonlinear influences are very similar in both groups and cancel out. Of course, although rare in FDI analysis, a regression specification could include the relevant nonlinear terms that would avoid bias. Conversely, a PSM specification might not adequately match treated and controls and thus fail to approximate a randomized controlled trial. It follows that the advantage of PSM regarding nonlinearity is not guaranteed.

The PSM procedures we use are those in the module *pscore* (Becker and Ichino, 2002), which can be installed in the statistics program Stata. We designate one exchange rate regime as the treatment, and various countries in various years (country/year combinations) experienced the treatment. Country/year combinations under a different regime are the controls. We will call the country/year combinations "units." An example of a unit would be "Tunisia in 1990." Standard PSM examines the binary case situation of treatment or lack of treatment, but we have three possibilities—fixed, intermediate, and floating or freely falling—from each of our definitions, LYS and RR. PSM can be applied simultaneously to multiple treatments (Imbens, 2000; Lechner, 2001), but an approach that is at least as good (according to Lechner, 2001, and Caliendo and Kopeinig, 2008) is to examine all possible binary cases. Therefore, we use the all-possible-binary-cases approach. For LYS, the binary cases are fixed and floating, intermediate and floating, and fixed and intermediate. For RR, the binary cases are the same, except that only the freely-falling subset of floating is used.

Given the treatment and the control regimes, *pscore* estimates the ATT, the average treatment effect on the treated. In the present application, the ATT is the effect on FDI of the treatment regime for those units that adopted the regime relative to what FDI would have been had the same units adopted the control regime instead. In PSM, there also exists a measure called the ATU, the average treatment effect on the untreated. In our case, this would measure what FDI would have been under the treatment regime relative to that under the control regime had the control units adopted the treatment regime. We can estimate the ATU in *pscore* by reversing the definition of treatment and control regime and taking the negative of the resulting ATT estimate.

4. Data and method

4.1. Variables and sample sizes

We specify FDI as the net inflow of FDI into the country, measured in percent relative to the country's GDP for the given year (as in Abbott et al., 2012). The data are annual. Using aggregate FDI as the response variable is consistent with using an aggregate treatment variable, which the LYS and RR regime definitions are. All determine a single regime type for any given country and year. But in a multi-country world, it is unlikely that a given country will have a regime type that applies to its exchange rate with all other countries. For instance, a country may float with some but fix with others. Such an arrangement is neither purely fixed nor purely floating in the aggregate, nor does it readily fall into any of the intermediate regime definitions.[3] It is thus unlikely that the empirical aggregate exchange rate regimes will perfectly match relatively simple definitions. Our empirical use of the LYS and RR definitions may therefore suffer from some level of aggregation bias.

But the problem is difficult to escape. For example, Busse et al. (2013) examine not aggregate but bilateral FDI in response to aggregate RR *de facto* regime definitions. But in so doing there could be bilateral FDI flows matched with inappropriate aggregate regime definitions, and so

[3] In fact, it is impossible for one country to fix with all others, and thus present a pure aggregate fixed regime, unless countries all fix with each other. Consider the 3-country case with currencies (in logs) of A, B, and C. Movements among the exchange rates are governed by: var(BC) = var(AB) + var(AC) – 2cov(AB,AC), where, for example "BC" means units of B per unit of C. If A is fixed with B and C, then all the right-hand terms equal 0 and thus var(BC) = 0 and B must be fixed with C. The preceding is true for any set of 3 countries, and must therefore hold for any larger set of countries, as such a set can always be broken down into groups of 3.

specification error remains possible. Moreover, the bilateral approach leads Busse et al. (2013) to have a very large fraction (three fourths) of zero FDI values. Dorn and Egger (2013), in their analysis of exchange rate regimes and trade flows, address the problem by using the approach of Klein and Shambaugh (2008).[4] A bilateral rate is defined as fixed for a given year if the rate never strays outside a ±2 percent band for that year. Thus, the fixed rate definition is quite clean, but the non-fixed category includes many alternatives. Thus, again, specification error is possible. Dorn and Egger (2015) use bilateral trade flows but the RR aggregate regime definitions. Unlike Busse et al. (2013), Dorn and Egger (2015) take into account the RR regimes of both countries when defining the regime to apply to a particular bilateral case, but the aggregation-bias possibility remains. Overall, we believe that there is presently no good argument in favor of one approach over another.

The choice of right-hand variables for specification of the logit equation must be made in light of several conditions. One is "unconfoundedness" (Rosenbaum and Rubin, 1983). If it holds, "given a set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment" (Caliendo and Kopeinig, 2008, p. 35). Endogeneity of right-hand variables must thus be absent from the logit equation, and confounders must be controlled for by including them in the equation. Since the confounders are selected so as to not be affected by the treatment (exchange rate regime) and thus are not affected by its probability, the confounders also cannot be affected by the outcome (FDI) of the treatment. There is thus no endogeneity problem as could arise under the regression approach.

An implication of unconfoundedness is that "the variables (X) on which [affect treatment] must be observable to the researcher" (Heinrich et al., 2010) and (of course) used by the researcher. Caliendo and Kopeinig (2008, p. 38) advise that "[o]nly variables that influence simultaneously the participation decision [here, choice of exchange rate regime] and the outcome variable [FDI] should be included." These are sometimes called true confounders (Austin, 2011).

[4] Dorn and Egger (2013) present the only other analysis of exchange rate regime effects we know of using PSM.

However, how the unconfoundedness condition should govern variable choice is sometimes modified. Austin (2011) discusses four possible sets of covariates: (1) all covariates that affect either treatment probability or outcome; (2) covariates that affect treatment probability; (3) covariates that affect outcome (potential confounders); and (4) covariates that affect both treatment probability and outcome (true confounders). Consistent with the argument of Rubin and Thomas (1996), Brookhart et al. (2006) provide simulation evidence in favor of using the potential confounders. Austin et al. (2007) find that using either the potential confounders or the true confounders is better than using either of the other two sets. On the other hand, Deuss's (2012) application is an example that argues for covariates affecting the treatment probability, which, according to Austin (2011), does have theoretical justification. A more fundamental problem is uncertainty about which possible covariates are, indeed, confounders of any sort. Omitting important variables or including unneeded variables can both cause problems, so both full and parsimonious specifications have supporters (Caliendo and Kopeinig, 2008). These issues are, of course, also important in regression analysis.

There is also the "overlap" or "common support" condition. Caliendo and Kopeinig (2008) discuss the formal details. Analysis is restricted to units with at least some chance of being both treated and not treated; the condition can be modified for computing the ATT. In *pscore*, for the ATT Becker and Ichino (2002, p. 366) use all treated units plus those controls in the region of common support. The common support condition provides another reason for preferring PSM to standard regression methods that rely on functional form to extrapolate outside the region of common support and that may, therefore, lack robustness in cases of poor overlap in support between the treated and the non-treated (Black and Smith, 2004). PSM thus reduces the dependence of results on the model or functional form chosen.

Our starting point for variables to include is the list used by Abbott et al. (2012). They run SYS-GMM regressions of FDI on a constant, two exchange rate regime dummies, and 12 other variables: trade openness, informational structure, natural resources, inflation, economic growth, government stability, investment profile, capital openness, educational attainment, efficiency wage relative to other developing countries, the real exchange rate, exchange rate volatility, and time dummies. Note that, as in Abbott et al. (2012), we include not only exchange rate regime but also exchange rate volatility, measured with respect to the U.S. dollar exchange rate. Although regime and volatility are naturally related to each other, in the empirical application they are not the same. For example, regimes deemed "floating" can have different amounts of volatility, as can intermediate regimes and even regimes deemed "fixed," given that the latter will almost surely not actually be fixed to all currencies. Also, the exchange rate regime may better signal to firms the likely exchange rate volatility applicable to a contemplated direct investment than does recently observed volatility.[5]

We revise the Abbott et al. (2012) variable list. First, to lessen the complexity of the logit equation, we change the time dummy specification to a linear time trend. The trend is the same for all countries because specifying as many time trends as there are countries would entail an absurdly large number of variables in the logit equation. Next, the efficiency wage variable is no longer available, so we substitute a labor productivity variable, real GDP per employed person. Next we add the host country real interest rate. Thus, we add a capital variable to the labor productivity variable (capital cost is important in Cushman, 1985, 1988; Love and Lage-Hidalgo, 2000; Yang et al., 2000; Çeviș and Çamurdan, 2007). Are there other needed variables? Blonigen and Piger (2014) use Bayesian averaging to determine covariates that have the most consistent empirical effects on FDI across many countries. The few resulting variables that are not already on our list often involve source-country variables. But properly aggregating these variables to be explainers of aggregate FDI inflows to developing countries would not be straightforward. However, two gravity variables noted as important by Blonigen and Piger (2014) are available. The first is host country real GDP in U.S.

[5] As described in the Appendix, our exchange rate volatility variable is computed using the country's bilateral rate against the U.S. dollar. It might be preferable to use trade (or investment) weighted multilateral effective exchange rates for these measures, but they are not available for our countries.

dollars (encouraging FDI as in De Vita and Kyaw, 2008). The second is remoteness (GDP-weighted distance from the world market). Finally, we include lagged FDI. FDI projects could be spread out over several years. Lagged FDI is also employed to capture the effect of agglomeration economies since foreign investors may be attracted to countries with more existing FDI.[6] At this point, the variables listed so far have been considered for their role as potential confounders, assumed to affect the outcome, FDI.

Now suppose that, instead of the potential confounders, we are interested in the true confounders. We need to make sure we have covariates that affect treatment probability. Juhn and Mauro (2002) report little regularity across countries in the variables that affect regime choice. Rogoff et al. (2003) summarize the finding by noting that only economic size and trade openness are consistently significant. Economic size (real GDP) and trade openness are already on our list. Many other variables on our list have also been considered by various papers as possibly affecting regime choice, according to Rogoff et al. (2003). For example, exchange rate volatility has been so considered, and thus belongs on our list as a true confounder, not just as a potential one. However, productivity, interest rates, investment profile, remoteness, time trend, and lagged FDI have not been previously considered as exchange regime determinants. Therefore, our list is best considered to consist of potential confounders, with a subset constituting the true confounders.

There is another variable that surely affects regime choice: lagged regime choice. Including it captures inertia and lagged response. Therefore, lagged regime could be a true confounder. Now, each logit regression involves the choice between two regimes, which seems to suggest just one lagged regime dummy. Nevertheless, we need to include dummies for other lagged regimes in the data set. This is because sometimes the lagged regime is not the control regime in the pair. Suppose

[6] By mimicking past investment decisions by competitors in choosing where to invest and co-locating, foreign investors seek to benefit from positive spillovers from investors already in place (see De Vita and Abbott, 2007).

the data set includes R regimes. For a given pair of treatment and control regimes, we need $R - 1$ lagged regimes.[7]

We have noted that the covariates must not have been influenced by the treatment. We thus lag all the covariates in the logit regression. Variables cannot be influenced by events in the future. Also, a regime decision is unlikely to be made until after relevant information has become available.

Regarding lags of regimes, for LYS we use the lags of the treatment and control regimes under consideration (one could with equal validity substitute the omitted regime for one of the included ones). For RR, in principle four lagged regimes should be used (one less than the number of RR coarse regimes after combining categories 2 and 3). However, we do not include the lagged dual regime dummy as there are just too few positive realizations. Sometimes the computation of its coefficient is not even possible in the logit procedure.

Our data set runs from 1981 through 2013, and there are 70 countries. After lagging all right-hand variables one year in the logit equations, the maximum estimation period becomes 1982-2013. The number of country/year units is 2,240. But our actual sample sizes are smaller. To begin with, the number of observations involving any given pair of regimes is smaller because some country/year units involve other regimes. Next, the RR regime definitions stop in 2010. Finally, there are missing values for many variables for many country/year units. We report the resulting sample sizes in various tables below.

Another consideration influences our sample sizes. Poulsen and Huffbauer (2011) report that the Great Recession caused a decline in FDI across many countries that has been not only larger than after past recessions, but also much more persistent. The responses of FDI to exchange rate regimes could thus be substantially different in the final years of our sample in a way that is not accounted for by PSM and the computation of the ATT. Suppose we have groups A, B, X, and Y. Suppose A and B

[7] It does not matter which of the R regimes. The alternative to including a second lagged regime dummy would be to drop all observations preceded in time by the omitted control regimes, which reduces the number of observations.

are well matched with each other and occur before the recession. Suppose that X and Y are also well matched with each other but occur during and after the recession. A and X get treated while B and Y do not. The ATT computations for the full data period assume that the treatment effect affecting A is the same as that affecting X. But suppose that the recession changes the treatment response. The PSM/ATT computations do not account for this, even with recession dummies added to the propensity score equation. The resulting ATT will instead be an average of the two time-period effects. *Pscore* provides no way to separately estimate the ATT values or test the difference in the estimates. (In principle, we could separately estimate the effects in the two time periods, but there are not enough observations in the latter period to do this.) Thus, if we are interested in the response to treatment in the absence of an extraordinary recession, the PSM/ATT approach in *pscore* will fail us if the time periods are combined. Therefore, we report results for the ending date of 2007 as well 2010 (for RR regimes) and 2013 (for LYS regimes).[8]

Definitions of all variables, data sources, and a list of the countries are given in the Appendix. Descriptive statistics of several key variables are also provided. For example, the median percentages of FDI to GDP categorized by exchange rate regime are 1.5 to 2.0 percent.

4.2. Parsimonious models to increase sample size

The full model has 19 or 20 right-hand variables (and sometimes more, if higher powers of variables are added to achieve balancing—discussed in the next section). If some variables actually play no significant role in determining the exchange rate regime, there could be an efficiency gain from dropping them. Also, dropping variables with missing data allows larger sample sizes because the remaining variables seldom have exactly the same missing observations as the dropped ones.

[8] We checked the various logit equations for breaks jointly in 2007 (end of pre-recession period) and 1996 (half way through the pre-2007 sample period). Both constant and slope dummies were included. The break dummies were never jointly significant for either break point. Thus, if the Great Recession presents an estimation problem, it is likely to be of the sort we have discussed, and not addressed with a dummy specification for the logit in *pscore*.

We apply “sequential elimination of regressors” (Brüggemann and Lütkepohl, 2001), a version of general-to-specific modeling (e.g., Hendry and Krolzig, 2001). We first estimate the full logit model and then drop the least statistically significant variable. We estimate the resulting model and once again drop the least significant variable. The procedure is repeated until all remaining variables are reported as significant at some standard level; we use 0.10.[9] With each iteration we can usually increase the sample size, because the dropped variable’s missing values are no longer binding. Now, when a candidate model is eventually achieved with all p-values ≤ 0.10, a variable previously dropped might now be significant with the larger sample size, if that variable were added back. Therefore, at this stage we search for any such variables by adding each previously dropped variable to the candidate model and checking its p-value. That is, if the candidate model has k variables after dropping j variables, we examine j models with $k + 1$ variables in each. We then add to the candidate model the variable with the lowest p-value of any less than 0.10. If there is such a variable, we have a new candidate model, and we repeat the procedure.[10] The resulting parsimonious, or reduced, models have sample sizes as much as two times the size of the full models.

4.3. How estimation with pscore proceeds

Pscore begins by using logit (or probit) to estimate each unit’s (country/year’s) propensity score. *Pscore* then sorts the units according to the propensity scores and divides the result into k blocks (strata). We use the *pscore’s* default value of $k = 5$. The balancing condition is then checked. Within each block, the hypothesis of equal mean propensity scores for treated and untreated units is tested. If a block fails the test, it is split, perhaps repeatedly, until the hypothesis is accepted for each block. Next, the hypothesis of equal means of the distributions of each covariate for the treated and

[9] The lagged regime coefficients are tested jointly. An individual lag coefficient may thus appear insignificant in the final logit equation.
[10] Our approach of adding variables to a small model is similar to the procedure of Black and Smith (2004).

untreated is tested in each block.[11] There are five or more blocks and up to 20 covariates, so there are very many tests, and therefore we are likely to get some rejections even if all null hypotheses are true. This is the multiple-test problem (see Romano et al., 2010). To adjust for the problem, we apply a modified Bonferroni adjustment to the significance level proposed by Simes (1986).[12] If the balancing test fails for any covariate (we use the Simes-adjusted 0.05 level), the propensity score specification must be revised. We follow a suggestion of Dehejia and Wahba (2002), which is to add successively higher powers of the offending covariate(s) until the balancing test is passed.

The next step is to compare treated with control cases that have sufficiently similar propensity scores and covariate means. The difference in outcome (FDI) for each matched treated and control unit is computed, and the mean value is the ATT estimate. However, the choice of which of two regimes to call the treatment is arbitrary. Therefore, we then reverse the definitions of treated and controls (e.g., change treatment from fixed to floating, and control from floating to fixed), and re-compute the ATT. The result is (approximately) the negative of the ATU for the original treatment definition.[13] Thus, we consider the effect of a regime in situations when it was *not* adopted as well as when it was.

Pscore provides five matching estimators to determine matched units and compute the ATT: kernel (ATTk), two versions of nearest neighbor (ATTnd and ATTnw), radius (ATTr), and stratification (ATTs). These estimators use different ways of deciding which treated and control units are sufficiently similar to be matched for the computation of the ATT. See Becker and Ichino (2002)

[11] In principle, the balancing condition for the covariates is that the covariate distributions are the same for the treated and the untreated with similar propensity scores. At present, *pscore* tests for differences in means but not higher order moments.

[12] The Simes (1986) method compares the observed *p*-values of a set of tests with a significance level that is adjusted downward from the desired α value. Let the ordered *p*-values from small to large be P_1 to P_n. H_0 is rejected if $P_j \leq j\alpha/n$ for any j =1, ..., n. Cushman and Michael (2011) and Cushman (2016) find good size and power properties for this approach with five tests, but it is uncertain if the adjustment would still be reasonable for 100 or more tests in *Pscore'*s balancing tests in our application. Thus, to avoid excessive failures to reject, we truncate the number of tests in the formula at 25. (*Pscore* recognizes the multiple test problem, making an adjustment equivalent to assuming five tests.)

[13] Direct computation of the ATU would involve a slightly different adjustment for the overlap condition.

for a full description. They state, “None of them is *a priori* superior to the others” (p. 362) and suggest that using all would provide a robustness check. We follow this advice, with the following exception. With continuous variables among the covariates (as we have), ATTnd and ATTnw “should give equal results” (Becker and Ichino, 2002, p. 363). Thus, we don’t use ATTnw.

The estimated ATTs concern the mean effect of regime on FDI. *Pscore* also provides standard errors, analytical (where possible) and bootstrapped, and corresponding *t*-statistics for judging the statistical significance of the effects. But with so many tests, there is, once again, a multiple-test problem. Therefore, to conservatively evaluate the overall significance of various ATT and ATU results, we again apply the Simes (1986) correction.

5. Results

5.1. ATT Results

The ATT estimates are presented in Figures 1 through 8 and Tables 1 through 8. They contain the ATT values, confidence intervals, and p-values for the LYS and RR regime definitions for the full and reduced models, and for the full and pre-Great Recession periods. To explain the figures and tables, let us focus on Figure 1 and Table 1, which refer to LYS regimes and the full model estimated through 2013. Figure 1 contains six graphs of 95% confidence intervals for ATT values. The heading of each graph gives the pair of regimes under consideration: the first term is the treatment and the second is the control. That is, “float-int” means that “floating” is the treatment and “intermediate regime” is the control. The first row of graphs is for one regime of a pair as the treatment, and the second row is for the other regime as treatment.

Each graph presents four confidence intervals, one for each of the four ways of estimating ATT values. The order from left to right is ATTk, ATTnd, ATTr, and ATTs. In computing the confidence intervals and then p-values, we have to deal with the fact that *pscore* usually presents two alternative standard errors for a given ATT estimate. The first is an analytical standard error (which can usually, but not always, be computed) and the second is a bootstrapped standard error (which can always be computed).[14] Thus, two confidence intervals and two p-values are often possible for one ATT. But to reach a conclusion for a given ATT, we prefer to consider a single p-value, and so we use the Simes (1986) approach to generate one p-value in the relevant cases.[15]

In Figure 1, all ATT 0.95 confidence intervals include zero except for the nearest neighbor version in the "fix-int" case. Thus, only the fix-int case shows any standard statistical significance, and for only one test. However, from a Bayesian perspective, the evidence may be stronger. A classical *x* percent confidence interval is approximately a Bayesian *x* percent posterior probability interval under weak priors (Greenland and Poole, 2013). Consider the float-fix intervals. The confidence intervals lie largely on the negative side of zero, implying Bayesian posterior probabilities noticeably in excess of 0.50 for a negative effect of a floating regime on inward FDI. The float-fix graph thus suggests mild evidence in favor of negative effects from the floating regimes compared with fixing. Similarly, the int-fix graph suggests intermediate regimes are detrimental relative to fixed regimes.

Let us now turn to Table 1. It first presents the *mean* of the four ATT values for each regime pair and treatment definition. We focus on the mean rather than, say, the most significant ATT value or only significant ATT values, because estimates with significant p-values will overstate the true parameter value (if there is, indeed, an effect), particularly in situations of medium or low power, a point made by Ioannidis (2008). By focusing on the mean of all our estimates we attenuate this problem. For example, fixed regimes are estimated to have increased inward FDI as a percent of

[14] We perform 2000 replications for each bootstrapped result. All graphs have the same vertical dimensions to allow clearer comparison of effect magnitudes and interval widths. In a few cases one or both ends of the confidence interval are truncated to prevent the remaining intervals from appearing very small.

[15] This is a conservative approach because it tends to favor the larger, less significant p-value. But it does not necessarily ignore the smaller p-value. The Simes adjustment with two p-values doubles the smaller one and then compares the result with the initially larger p-value. The adjusted p-value is the smaller of the two compared values. Bodory et al. (2016) report that various bootstrap procedures generally provide better size and power than the analytical approach, and so we certainly want to take bootstrapped values into account. They are usually the smaller of the two initial p-values in our results, consistent with better power if the null hypotheses are indeed false.

GDP by 0.62 percentage points for the country/year cases that adopted them compared with what would have happened in those country/year units had they had an intermediate regime.

The next three lines of Table 1 present Simes p-values for various groups of the significance tests that correspond to the confidence intervals. To highlight classically significant values relative to non-significant values, p-values greater than 0.10 are reported to only two decimal places, while values less than or equal to 0.10 are reported to three decimal places, and those less than or equal to 0.05 are additionally boldface-italicized. Consider the fixed-intermediate case. The individual ATT p-values in Table 1corresponding to the confidence intervals in Figure 1 are 0.506, 0.020, 0.357, and 0.326. (All individual ATT values, *t*-statistics, and p-values are reported in the Supplementary file, available at the journal website.) Given the multiple-test problem, despite the 0.020 p-value do we really have a statistically significant result? The Simes (1986) adjustment gives a p-value of 0.081, mild standard significance. There are also larger groups of tests for which one might be interested in Simes *p*-values, for example, all eight tests for a regime pair however treatment is defined. For the fix-int and int-fix cases, the result is 0.16. And, finally, every confidence interval in Figure 1 implies a test of the null hypothesis that regimes do not matter. Therefore, we compute a Simes p-value for all 24 tests. The result is 0.49. Hence, according to the Simes approach and standard statistical significance, the evidence of regime effects in Figure 1 and Table 1 is very weak.

The final two lines of the table report the number of regimes available for each ATT computation. The sum for a given regime pair is the sample size for the logit regression. However, the numbers of treatment and control regimes used after implementation of the common support condition and the various matching procedures are often smaller. See the online Supplementary file.

Having elaborated on interpretations of the graphs and tabular values in Figure 1 and Table 1, let us move on to the overall results. For the full period ending in 2013, the LYS results suggest more FDI under relatively fixed regimes than under relatively flexible rates, by as much as 0.81 percentage points, but generally less. Statistical significance is, in any event, quite weak, mostly based on the

0.081 fix-int p-value in Table 1, noted above, and the consistency of float-fix confidence intervals on the negative side in Figure 2. However, when the period is truncated to end in 2007, the sizes and significances of the ATT estimates for how much higher FDI is under relatively fixed regimes are larger and more statistically significant. The size effect becomes as large as 1.2 percentage points. For statistical significance, note the Figure 3 full-model float-fix and int-fix confidence intervals and Table 3 float-fix p-values of 0.022 and 0.044. Nevertheless, the overall Simes p-value for the 24 full-model tests is only 0.13. Also, the corresponding reduced-model effects of Figure 4 and Table 4 are less significant. The large decline in the size and significance of positive effects of relatively fixed regimes on FDI using the period ending in 2013 compared to using the period ending in 2007 is consistent with our conjecture that the Great Recession changed responses.

The RR regime results present a stronger case that relatively fixed rates encourage inward FDI. Consider the full estimation period available for RR regimes (through 2010). FDI is higher by as much as 1.5 percentage points. In terms of statistical significance, the superiority of relatively fixed regimes rests first on the freely falling-intermediate case in Table 5 (p-value of 0.022) and the fixed-freely falling and freely falling-intermediate cases in Table 6 (p-values of 0.003 to 0.008). Although for the full models of Table 5 the Simes p-value for all 24 tests is only 0.13, for the reduced models of Table 6 it is 0.019. Also, the Bayesian interpretation of the confidence intervals in Figures 5 and 6 is also consistent with relatively fixed regimes encouraging FDI in most of the graphs in Figures 5 and 6 (the only clear exceptions being int-fix in Figures 5 and 6 and ff-int in Figure 6).[16]

In contrast to the LYS results, the RR results that relatively fixed regimes are associated with higher FDI are *more* statistically significant in the data sets that include the Great Recession and its aftermath than those including only the pre-Great Recession period. Moreover, the signs of the ATT

[16] The freely falling (ff) regimes are the ones associated with the statistically significant RR results but by definition are also high-inflation countries. Do our ff regime findings actually reflect the effect of inflation, one of our confounding variables? The concern is addressed by the balancing tests, and the *pscore* balancing tests are indeed satisfied. One reason would likely be that in many cases non-ff countries also have high inflation.

estimates in the tables are the same and usually the magnitudes are similar for the two estimation periods and for the full and reduced models, unlike for the LYS results. Furthermore, the RR regime sign effects always accord with relatively fixed regimes encouraging inward FDI. The consistency of the ATT estimates between the two estimation periods and the greater significance for the longer period are consistent with additional data adding power to the tests, rather than a change in structure as suggested by the LYS results. Thus it is unclear whether the Great Recession affected regime response, or whether the discrepancies between the LYS and RR estimates reflect different regime definitions or other factors. Resolving this anomaly remains for future research.[17]

5.2. A different measure of the economic magnitude of the ATT estimates

The ATT estimates give percentage point differences in FDI relative to GDP between different regimes. But a one percentage point increase in FDI to GDP is more notable if FDI to GDP is only two percent than if it is 50 percent. Table 9 for LYS regimes and Table 10 for RR regimes present various results for the following measure:

$$100 \ln\{ [ATT/100] / [(FDI/GDP)_{median} – ATT/100] + 1 \}.$$

This is the percentage change in FDI/GDP in response to the treatment regime (the ATT) relative to median FDI/GDP in the absence of the treatment regime for the country-year units used to compute the ATT.[18] The "a" parts of Tables 9 and 10 give individual regime comparison values corresponding to the ATT values in Tables 1-8. In Table 9 (a), for example, and according to the full model ending in 2013, LYS fixed regimes increase FDI/GDP by 45% relative to what the country/year units would have experienced under intermediate regimes. With one exception, all estimates in Tables 9 (a) and 10 (a) that are greater than 20 in absolute value are in accordance with the theory that relatively fixed regimes raise FDI. There are, however, also small or wrongly signed

[17] Inconsistencies among *de facto* regime classifications are well known (Eichengreen and Razo-Garcia, 2013).
[18] We use medians instead of means because the FDI/GDP values are highly skewed from a few very large values.

effects (although the wrongly signed effects are never associated with statistically significant ATT values). The variation suggests treating the Table 9 (a) and 10 (a) estimates with caution.

To give a broader depiction of the effects, the "b" parts of Tables 9 and 10 present the mean effects of the relatively fixed regimes for each pair of regime definitions with each as both treatment and control. For example, the RR result in Table 10 (b) for the full model ending in 2010 shows intermediate regimes with 56% higher FDI/GDP than freely falling regimes (56 is the mean of 43 and abs(-70) from part (a)). The Tables 9 (b) and 10 (b) means are conservative in that their computation uses not only statistically significant but also non-statistically significant values. Thus, they reduce the overestimate of effect magnitude noted by Ioannidis (2008) from using (only) statistically significant estimates.[19] The means usually indicate that relatively fixed regimes are associated with higher FDI/GDP. The effects are large for the RR regimes.

For overall estimates, we compute the means of the regime pair means across the various models and estimation periods. These are the column means of Tables 9 (b) and 10 (b). The impacts of relatively fixed LYS regimes on FDI are not large. Fixed relative to floating regimes give an overall estimate of 14% higher FDI, and fixed relative to intermediate regimes give 11% higher FDI. Intermediate relative to floating regimes show a contradictory negative effect of 10%. In contrast, the RR regime effect estimates are large. Fixed regimes raise FDI by 69% relative to freely floating, intermediate regimes raise FDI by 48% relative to freely floating, and fixing raises FDI by 30% relative to intermediate regimes.[20] However, only the first two of these impact values, those involving freely floating regimes, have statistically significant results underlying them.

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[19] In fact, the individual estimates in Tables 9 (a) and 10 (a) are also conservative in this way, as the ATT values used to construct them are also means computed from sometimes statistically insignificant values, as mentioned in section 5.1.

[20] In several instances, the number of RR control regimes ultimately used to compute the ATT and its statistical significance is very small; this can be seen in the online Supplementary file. None of these instances, however, contribute to any of the statistically significant p-values we report for RR regime comparisons.

5.3. The logit results for regime determinants

If the logit models determining the propensity scores make economic sense, then the credibility of the ensuing ATT results is enhanced. We therefore present a summary of the logit results. Table 11 shows the signs of variables significant at the 0.10 level in the full models when the dependent variable is the relatively fixed regime in the pair.[21] We do not include the actual logit coefficient values because this would add substantial but unimportant detail. Table 12 shows the variables that survive in the reduced specifications with larger sample sizes. The tables also give the means of proportions of correct treatment and control regime predictions (Kennedy, 2003, p. 267). Values in excess of 0.50 indicate predictive accuracy greater than chance.[22] The values in the table almost always exceed 0.80. Finally, sample sizes are included.

Trade openness, capital openness, education, economic size, and remoteness appear as significant or as survivors most often in the tables. Trade openness shows the theoretical negative relationship with relatively fixed regimes, which is also consistent with past empirical work (see, e.g., Rogoff et al., 2003). Capital openness has a consistent positive relationship with relative fixing. This, however, does not entirely match discussion by Juhn and Mauro (2002), who note that capital openness is thought to impel countries toward the endpoints of hard fixes and pure floats. Education, not normally on lists of regime affecters, has a negative relationship with relative fixing. Economic size and remoteness, meanwhile, need to be jointly considered because their correlation is very high ($r = 0.96$), reflecting that the remoteness variable is partly constructed from economic size. Their separate effects are therefore difficult to disentangle. Thus, the sometimes positive sign of economic size in our tables does not necessarily contradict the theoretical expectation and empirical findings of a negative relationship with fixing (Juhn and Mauro, 2002). In fact, every time the economic size

[21] If the regime dummy definition is reversed to indicate the relatively floating regime and the right-hand variable list is the same, then all coefficient values are the same but with reversed signs. So there is no need to report both.
[22] Kennedy (2003) specifically recommends the *sum* of the proportions of correct treatment predictions and correct control predictions, with values over 1.0 indicating predictive accuracy greater than chance. We think it more natural to compute the mean, a fraction between zero and one, where values greater than 0.50 are meaningful.

effect is positive, the expected negative effect appears to have been captured by remoteness. In sum, the logit results are essentially consistent with theory and past empirical results. This, we think, increases the credibility of our conclusions concerning regime effects on FDI.

6. Conclusion

Using propensity score matching and up to 33 years of data, in accordance with theory we find evidence that *de facto* relatively fixed exchange rate regimes are associated with more direct investment into developing countries than are *de facto* relatively floating regimes. Using the RR regime definitions, the effect is seen for every binary comparison across two estimation periods and several propensity score model specifications. The strongest evidence comes from the longer RR estimation period and parsimonious models. The combined p-value for all the RR regime comparisons is fairly significant (p-value = 0.019) using a conservative approach to p-values that accounts for the multiple test problem. The significance of relatively fixed RR regime effects is also supported by the Bayesian interpretation of the confidence intervals. The response magnitudes are often large, with FDI sometimes estimated to be higher under relatively fixed RR regimes by well over 50%. However, given the wide variation among the RR response magnitudes taking all into account, the very large magnitudes should be viewed cautiously. We address the problem, ultimately, by computing the means of the effects for each regime pair comparison across all the models and estimation periods. The resulting estimates are indeed attenuated, but remain large, from 30 to 69%. In terms of statistical significance, freely falling regimes are clearly the detriments to FDI, in that the statistically significant results do not involve comparisons of fixed with intermediate regimes.

Compared with the RR results, effects estimated using the LYS regime definitions are less consistent in sign, less statistically significant, and much smaller. The combined p-value for the most significant set of regime comparisons, for the full model using pre-Great Recession data, is only 0.13. Nevertheless, a Bayesian interpretation of the confidence intervals lends some support to relatively fixed LYS regimes encouraging FDI. And the three individual comparisons with at least a 0.10 level of statistical significance are in accord with relatively fixed regimes encouraging FDI. The most significant individual comparison (p-value = 0.022) is for floating instead of fixing, showing the theoretically expected negative effect.

The choice of exchange rate regime by a developing country, of course, cannot rest solely on its FDI-inducing properties, growth-promoting though FDI may be, since such a choice affects and is influenced by many factors (current account imbalances, inflation rates, the availability of international reserves, and macroeconomic stabilization to name but a few). Nevertheless, the core policy implication for developing countries considering the relative merits of alternative exchange rate regimes is that FDI responses are important.

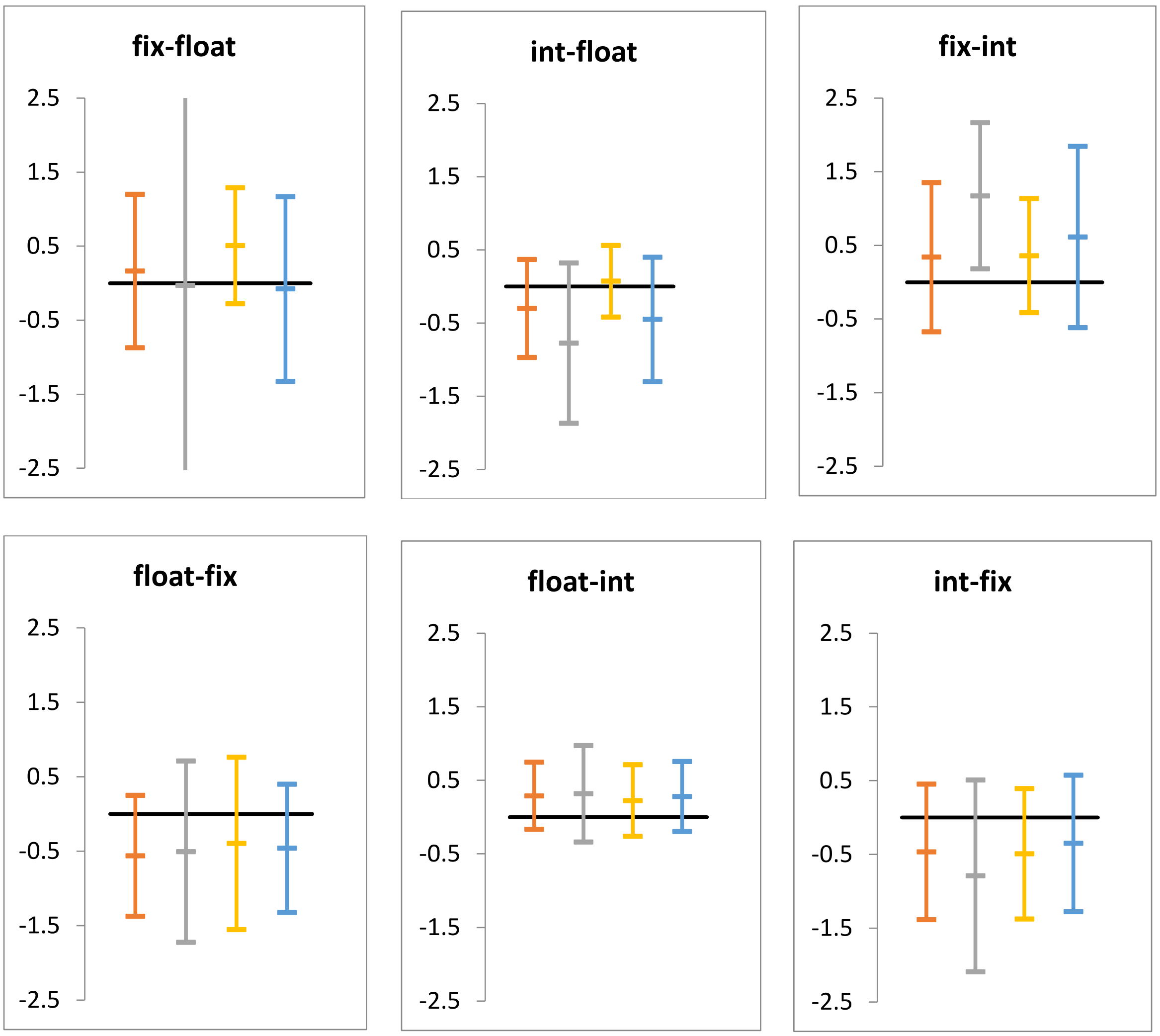

Fig. 1. LYS regimes: ATT 95% confidence intervals for full models through 2013.

Table 1
LYS regimes: Mean ATTs and Simes p-values for full models through 2013.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-float</th><th>float-fix</th><th>int-float</th><th>float-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>0.14</td><td>-0.48</td><td>-0.36</td><td>0.28</td><td>0.62</td><td>-0.52</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.81</td><td>0.50</td><td>0.50</td><td>0.36</td><td>0.081</td><td>0.42</td></tr>
<tr><td colspan="2">0.79</td><td colspan="2">0.43</td><td colspan="2">0.16</td></tr>
<tr><td colspan="6">0.49</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>307</td><td>int =</td><td>293</td><td>fix =</td><td>307</td></tr>
<tr><td>float =</td><td>435</td><td>float =</td><td>435</td><td>int =</td><td>293</td></tr>
</table>

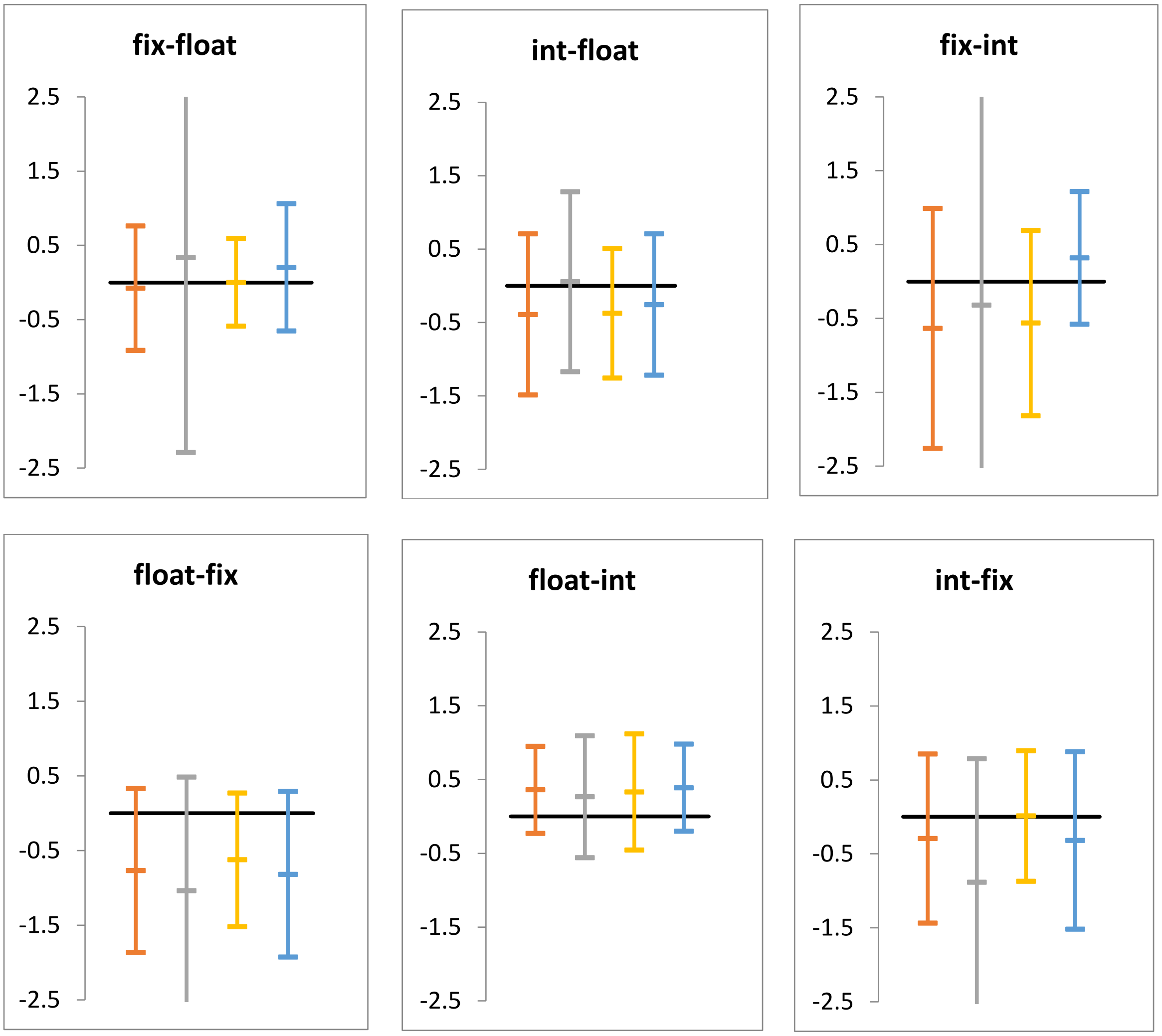

Fig. 2. LYS regimes: ATT 95% confidence intervals for reduced models through 2013.

Table 2
LYS regimes: Mean ATTs and Simes p-values for reduced models through 2013.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-float</th><th>float-fix</th><th>int-float</th><th>float-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>0.12</td><td>-0.81</td><td>-0.24</td><td>0.34</td><td>-0.30</td><td>-0.37</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.99</td><td>0.18</td><td>0.80</td><td>0.45</td><td>0.64</td><td>0.82</td></tr>
<tr><td colspan="2">0.36</td><td colspan="2">0.69</td><td colspan="2">0.82</td></tr>
<tr><td colspan="6">0.85</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>471</td><td>int =</td><td>458</td><td>fix =</td><td>530</td></tr>
<tr><td>float =</td><td>568</td><td>float =</td><td>584</td><td>int =</td><td>418</td></tr>
</table>

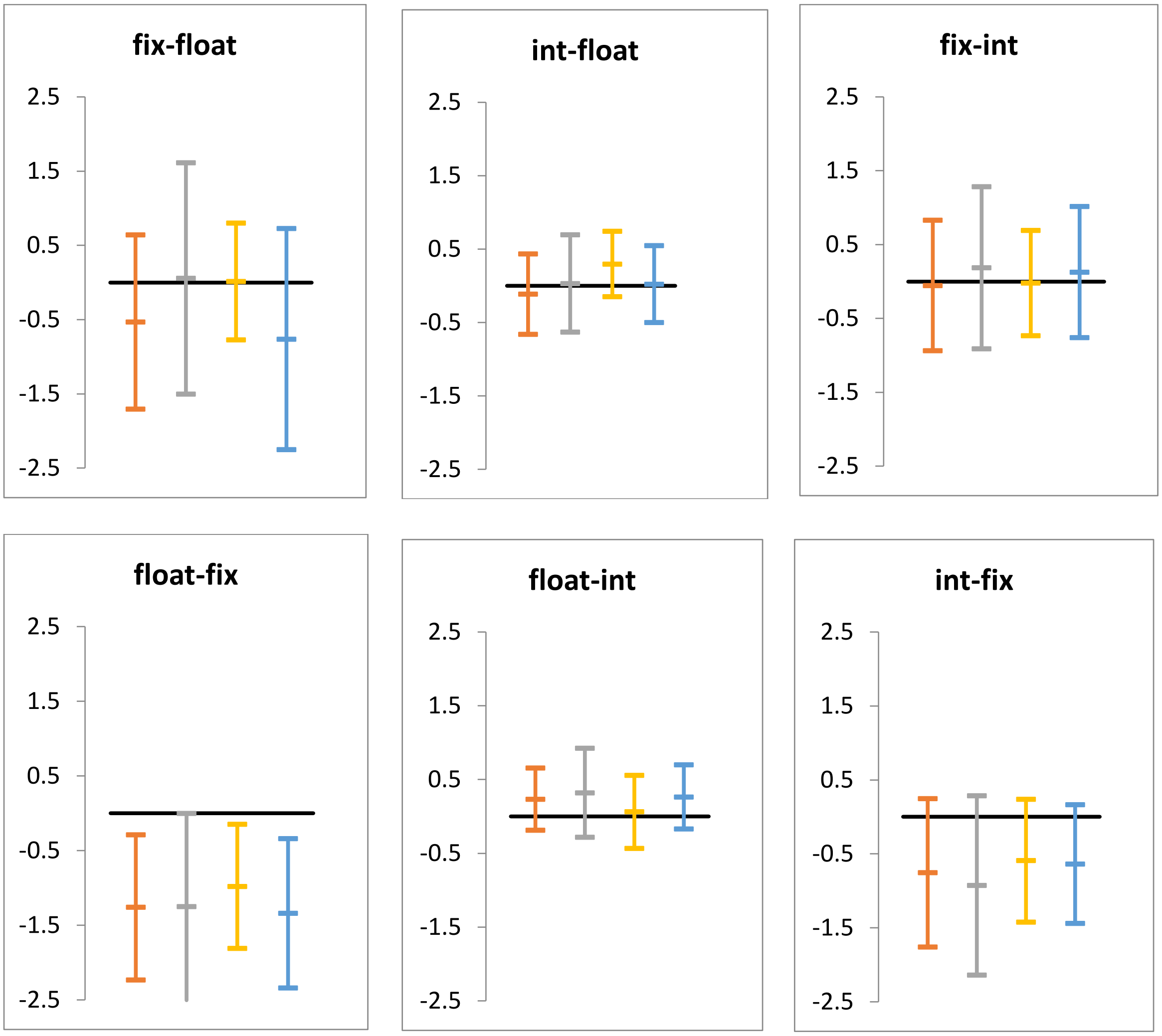

Fig. 3. LYS regimes: ATT 95% confidence intervals for full models through 2007.

Table 3
LYS regimes: Mean ATTs and Simes p-values for full models through 2007.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-float</th><th>float-fix</th><th>int-float</th><th>float-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>-0.30</td><td>-1.21</td><td>0.06</td><td>0.22</td><td>0.06</td><td>-0.73</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.75</td><td>0.022</td><td>0.76</td><td>0.39</td><td>0.95</td><td>0.16</td></tr>
<tr><td colspan="2">0.044</td><td colspan="2">0.59</td><td colspan="2">0.32</td></tr>
<tr><td colspan="6">0.13</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>229</td><td>int =</td><td>225</td><td>fix =</td><td>229</td></tr>
<tr><td>float =</td><td>313</td><td>float =</td><td>313</td><td>int =</td><td>225</td></tr>
</table>

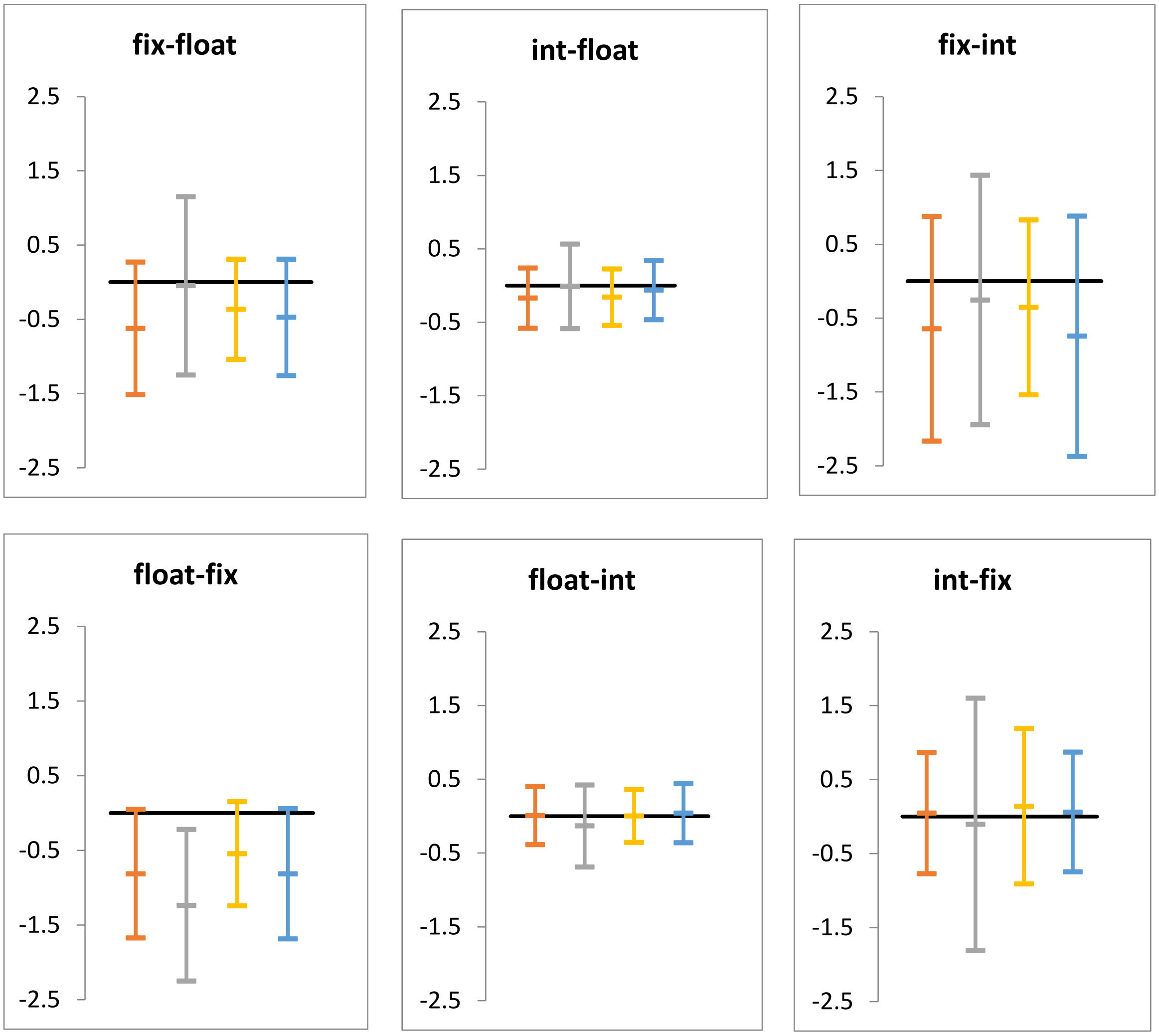

Fig. 4. LYS regimes: ATT 95% confidence intervals for reduced models through 2007.

Table 4
LYS regimes: Mean ATTs and Simes p-values for reduced models through 2007.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-float</th><th>float-fix</th><th>int-float</th><th>float-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>-0.38</td><td>-0.85</td><td>-0.10</td><td>-0.02</td><td>-0.50</td><td>0.04</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.38</td><td>0.068</td><td>0.83</td><td>0.98</td><td>0.74</td><td>0.91</td></tr>
<tr><td colspan="2">0.14</td><td colspan="2">0.98</td><td colspan="2">0.91</td></tr>
<tr><td colspan="6">0.41</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>389</td><td>int =</td><td>369</td><td>fix =</td><td>514</td></tr>
<tr><td>float =</td><td>413</td><td>float =</td><td>431</td><td>int =</td><td>415</td></tr>
</table>

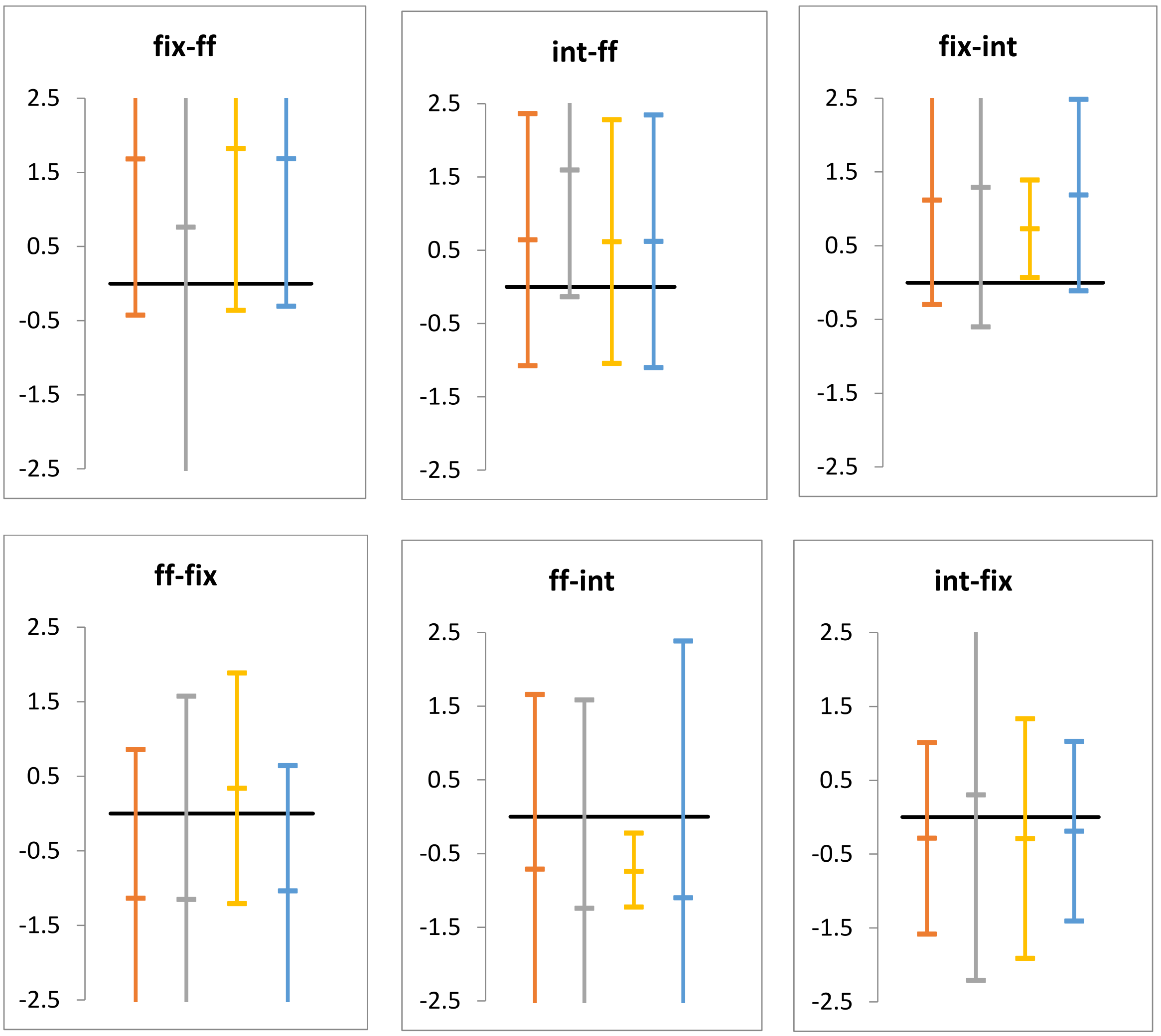

Fig. 5. RR regimes: ATT 95% confidence intervals for full models through 2010.

Table 5
RR regimes: Mean ATTs and Simes p-values for full models through 2010.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-ff</th><th>ff-fix</th><th>int-ff</th><th>ff-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><th>Mean ATT</th><td>1.49</td><td>-0.75</td><td>0.87</td><td>-0.95</td><td>1.08</td><td>-0.11</td></tr>
<tr><th rowspan="3">Simes p-values</th><td>0.16</td><td>0.53</td><td>0.28</td><td>0.022</td><td>0.12</td><td>0.81</td></tr>
<tr><td colspan="2">0.31</td><td colspan="2">0.043</td><td colspan="2">0.23</td></tr>
<tr><td colspan="6">0.13</td></tr>
<tr><th rowspan="2">Number of regimes</th><td>fix =</td><td>249</td><td>int =</td><td>655</td><td>fix =</td><td>249</td></tr>
<tr><td>ff =</td><td>67</td><td>ff =</td><td>67</td><td>int =</td><td>655</td></tr>
</table>

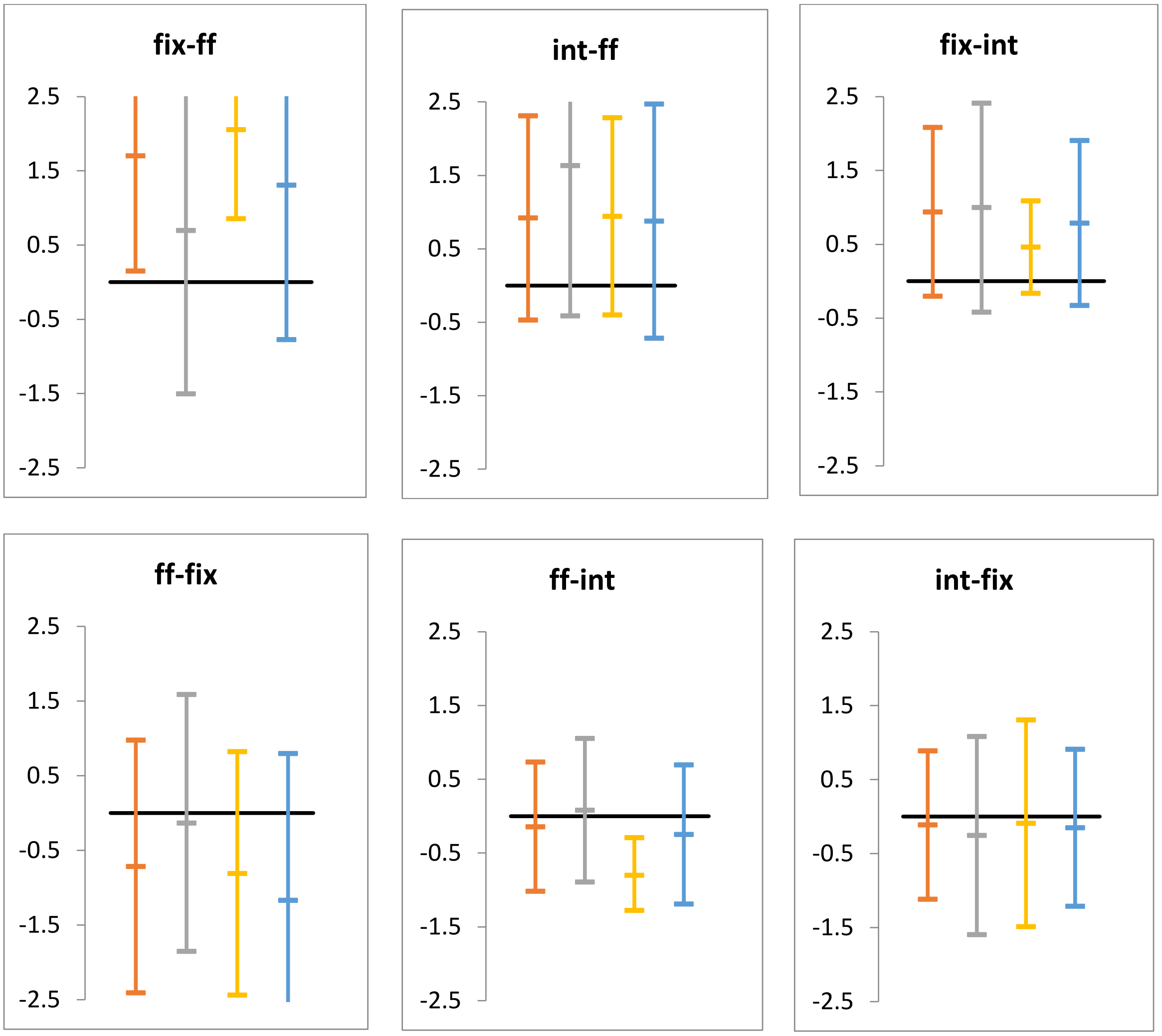

Fig. 6. RR regimes: ATT 95% confidence intervals for reduced models through 2010.

Table 6
RR regimes: Mean ATTs and Simes p-values for reduced models through 2010.

	Treatment regime-control regime					
	fix-ff	**ff-fix**	**int-ff**	**ff-int**	**fix-int**	**int-fix**
Mean ATT	1.44	-0.70	1.09	-0.28	0.80	-0.15
Simes p-values	***0.003***	0.54	0.26	***0.008***	0.17	0.90
	0.006		***0.017***		0.33	
	0.019					
Number of regimes	fix =	397	int =	737	fix =	407
	ff =	121	ff =	85	int =	912

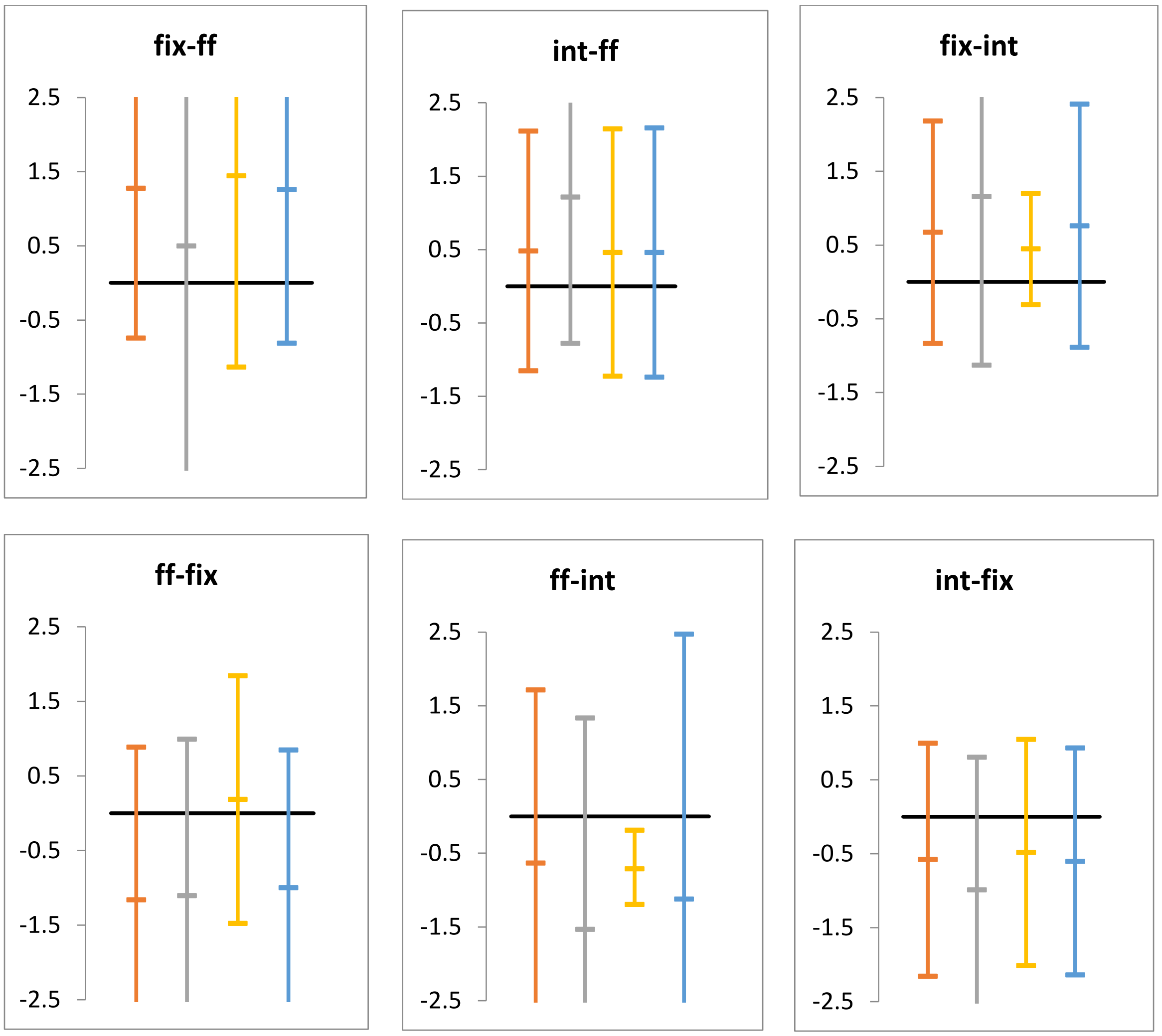

Fig. 7. RR regimes: ATT 95% confidence intervals for full models through 2007.

Table 7
RR regimes: Mean ATTs and Simes p-values for full models through 2007.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-ff</th><th>ff-fix</th><th>int-ff</th><th>ff-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>1.12</td><td>-0.77</td><td>0.65</td><td>-1.00</td><td>0.76</td><td>-0.66</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.36</td><td>0.41</td><td>0.59</td><td>0.032</td><td>0.38</td><td>0.53</td></tr>
<tr><td colspan="2">0.41</td><td colspan="2">0.064</td><td colspan="2">0.53</td></tr>
<tr><td colspan="6">0.19</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>198</td><td>int =</td><td>558</td><td>fix =</td><td>198</td></tr>
<tr><td>ff =</td><td>67</td><td>ff =</td><td>67</td><td>int =</td><td>558</td></tr>
</table>

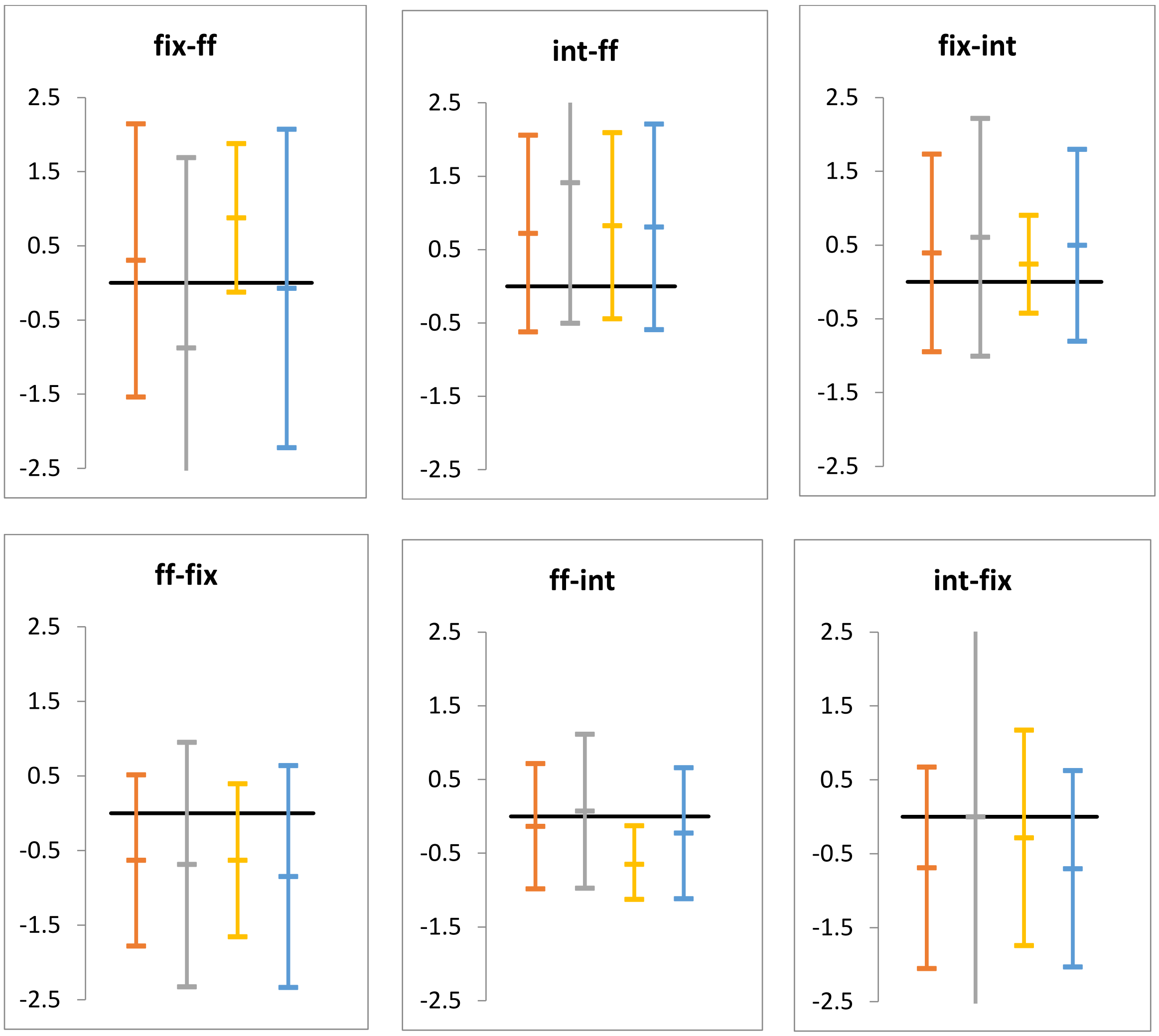

Fig. 8. RR regimes: ATT 95% confidence intervals for reduced models through 2007.

Table 8
RR regimes: Mean ATTs and Simes p-values for reduced models through 2007.

<table>
<tr><th></th><th colspan="6">Treatment regime-control regime</th></tr>
<tr><th></th><th>fix-ff</th><th>ff-fix</th><th>int-ff</th><th>ff-int</th><th>fix-int</th><th>int-fix</th></tr>
<tr><td>Mean ATT</td><td>0.06</td><td>-0.70</td><td>0.94</td><td>-0.23</td><td>0.44</td><td>-0.42</td></tr>
<tr><td rowspan="3">Simes p-values</td><td>0.34</td><td>0.37</td><td>0.29</td><td>0.059</td><td>0.56</td><td>0.64</td></tr>
<tr><td colspan="2">0.56</td><td colspan="2">0.12</td><td colspan="2">0.75</td></tr>
<tr><td colspan="6">0.35</td></tr>
<tr><td rowspan="2">Number of regimes</td><td>fix =</td><td>408</td><td>int =</td><td>629</td><td>fix =</td><td>410</td></tr>
<tr><td>ff =</td><td>181</td><td>ff =</td><td>85</td><td>int =</td><td>877</td></tr>
</table>

Table 9
LYS regimes: ATT values as percentages of median FDI/GDP
(a) Individual values with each regime as treatment then control

	treatment regime-control regime					
model, ending date	**fix-flo**	**flo-fix**	**int-flo**	**flo-int**	**fix-int**	**int-fix**
full, 2013	9	-21	-21	15	45*	-29
reduced, 2013	6	-32	-12	17	-15	-16
full, 2007	-16	-46**	4	11	3	-40
reduced, 2007	-20	-38*	-7	-1	-28	3

(b) Means of the effect of the relatively fixed regime with each regime as treatment and control

	means		
model, ending date	**fix, flo**	**int, flo**	**fix, int**
full, 2013	15	-18	37
reduced, 2013	19	-14	1
full, 2007	15**	-4	22
reduced, 2007	9	-3	-15
column means	14	-10	11

Note: Asterisks indicate the level of statistical significance of the underlying ATT estimate, or pair of estimates underlying the means, * for the 0.10 level and ** for the 0.05 level

Table 10
RR regimes: ATT values as percentages of median FDI/GDP
(a) Individual values with each regime as treatment then control

	treatment regime-control regime					
model, ending date	**fix-ff**	**ff-fix**	**int-ff**	**ff-int**	**fix-int**	**int-fix**
full, 2010	86	-58	43	-70**	54	-4
reduced, 2010	137***	-71	64	-26***	54	-7
full, 2007	63	-60	33	-72**	38	-25
reduced, 2007	4	-75	57	-22	33	-22

(b): Means of the effect of the relatively fixed regime with each regime as treatment and control

	means		
model, ending date	**fix, ff**	**int, ff**	**fix, int**
full, 2010	72	56**	29
reduced, 2010	104***	45**	30
full, 2007	61	53*	32
reduced, 2007	40	39	27
column means	69	48	30

Note: See note to Table 9, with the addition that *** indicates the 0.01 level.

Table 11
Signs of significant logit coefficients (0.10 level) and other logit statistics: full models.

	Regime Pairs											
variable (lagged except trend)	***LYS - 2013 end date***			***LYS - 2007 end date***			***RR - 2010 end date***			***RR - 2007 end date***		
	fix-flo	***int-flo***	***fix-int***	***fix-flo***	***int-flo***	***fix-int***	***fix-ff***	***int-ff***	***fix-int***	***fix-ff***	***int-ff***	***fix-int***
Time trend						−		+			+	−
Productivity			+					−			−	
Real int. rate								−			−	
Invest. profile												
Govt. stability												
Nat. resources	+			+								
Informat. str.					+			+			+	
Econ. growth									+			
Inflation		+			+			−				
Education	−	−		−	−			−			−	
Trade openness	+		+	+	+		+	+	+	+	+	+
Cap. openness		+		+			+	+		+	+	
Real ex. rate							+		+	+		+
Ex. rate volatil.		−			−							
FDI												
Economic size							+		+	+		+
Remoteness							−	+	−	−	+	−
Fixed regime	+	n/a	+	+	n/a	+	+		+	+		+
Interm. regime	n/a			n/a				+				
Flexible regime	−	−	n/a	−	−	n/a						
Correct predict.	0.88	0.68	0.82	0.87	0.71	0.80	0.95	0.89	0.96	0.94	0.88	0.95
Number of obs.	742	728	600	542	538	454	316	722	904	265	625	756
Fixed reg.	307	n/a	307	229	n/a	229	249	n/a	249	198	n/a	198
Interm. reg.	n/a	293	293	n/a	225	225	n/a	655	655	n/a	558	558
Flex. reg.	435	435	n/a	313	313	n/a	67	67	n/a	67	67	n/a

Notes: Blank cells indicate statistical insignificance. Signs are for the coefficient with the relatively fixed regime as dependent variable. "Correct predict." gives the mean of the proportions of correct treatment and control regime predictions. In several cases, the attempt to satisfy the balancing condition added variables to the logit as follows (the dependent variable is the first given in the regime pair, and balancing is then satisfied unless otherwise noted): LYS fix-float: real int. rate/trade cross product; balancing improves but still fails marginally. LYS float-fix: inflation squared and real int. rate squared; balancing improves but still fails, while real int. rate and inflation become significant, and education and trade become insignificant. LYS fix-int: could not satisfy or improve balancing tests. LYS int-fix: natural resources squared, and natural resources also becomes significant. RR int-ff and ff-int: real int. rate squared and cubed; remoteness becomes insignificant. RR ff-fix: std. deviation squared and cubed. RR int-ff, ff-int: real int. rate squared and cubed; inflation becomes significant.

Table 12
Signs of surviving logit coefficients and other logit statistics: reduced models.

	Regime Pairs											
Variable (lagged except trend)	***LYS - 2013 end date***			***LYS - 2007 end date***			***RR - 2010 end date***			***RR - 2007 end date***		
	fix-flo	***int-flo***	***fix-int***	***fix-flo***	***int-flo***	***fix-int***	***fix-ff***	***int-ff***	***fix-int***	***fix-ff***	***int-ff***	***fix-int***
Time trend					−	−	+	+		+	+	
Productivity			+				−	−			−	
Real int. rate								−			−	
Invest. profile		−						−	−		−	
Govt. stability							−					
Nat. resources	+			+	+							
Informat. str.								+			+	
Econ. growth									−			
Inflation								−	+		−	+
Education	−		−	−			−			−		
Trade openness	+		+				+	+		+	+	+
Cap. openness		+					+	+		+	+	
Real ex. rate	+		+			+						+
Ex. rate volatil.	+			+	+							
FDI									+			
Economic size	−	−		−		+	+	−		+	−	
Remoteness	+	+	−			−	−	+			+	
Fixed regime	+	n/a	+	+	n/a	+	+		+	+		+
Interm. regime	n/a		+	n/a		+		+	−		+	−
Flexible regime	−	−	n/a	−	−	n/a						
Correct predict.	0.89	0.69	0.82	0.88	0.70	0.81	0.93	0.87	0.96	0.93	0.87	0.96
Number of obs.	1039	1042	948	802	800	929	518	822	1319	589	714	1287
Fixed reg.	471	n/a	530	389	n/a	514	397	n/a	407	408	n/a	410
Interm. reg.	n/a	458	418	n/a	369	415	n/a	737	912	n/a	629	877
Flex. reg.	568	584	n/a	413	431	n/a	121	85	n/a	181	85	n/a

Notes: Blank cells indicate the variable did not survive the process of regressor elimination, except for lagged regimes, where a blank cell indicates individual insignificance although the lagged regimes were jointly significant. Signs are for the coefficient with the relatively fixed regime as dependent variable. "Correct predict" gives the mean of the proportions of correct treatment and control regime predictions. In several cases, the attempt to satisfy the balancing condition adds variables to the logit as follows (the dependent variable is the first given in the regime pair, and balancing is then satisfied): LYS fix-int and int-fix: remoteness squared. RR int-ff: inflation squared and cubed. RR fix-int and int-fix: inflation squared.

Appendix

1. Variable definitions and data sources *(WDI = World Development Indicators, IFS = International Financial Statistics)*[23]

FDI = Net FDI flows into the developing country as a percent of its GDP (*WDI*).

Trade openness = merchandise and service exports plus imports as a percent of GDP (*WDI*).

Informational structure = number of telephone subscriptions per 100 people (*WDI*).

Natural resources = percentage share of fuel and metal ore in total exports (*WDI*).

Inflation (measure of macroeconomic stability) = annual percentage change in GDP deflator (*WDI* and *IFS*).

Economic growth = annual percentage growth rate of real GDP (*WDI*).

Government stability = a risk rating estimating the ability of a government to carry out its declared policy programs as well as its ability to stay in office; higher numbers mean lower risk (*Political Risk Services*).

Investment profile = host country's attitude to international investment drawing from several indicators, including risk to operations, taxation, and repatriation of profits; higher numbers mean a more attractive profile (*Political Risk Services*).

Capital openness = index number measuring relative absence of institutional restrictions that a country places on current account and capital account transactions; higher numbers mean more openness (Chinn and Ito, 2006, 2008, and http://web.pdx.edu/~ito/Chinn-Ito_website.htm).

Educational attainment = average years of total schooling of those 25 years old and older (Barro and Lee, 2013, and http://barrolee.com/). The raw observations are at five-year intervals through 2010. We use interpolation (and extrapolation for 2011–2013) to fill in the gaps.

[23] In some cases, missing values are generated using interpolation or regression on related variables. Details available upon request.

Productivity = real GDP per employed person (computed from real GDP, population, and the employment to population ratio, *WDI*).

Real exchange rate = $r_{i,t}$ = real price of the U.S. dollar in terms of the developing country *i*'s real currency in time period *t*. We first compute *x* = developing country price of the U.S. dollar (*WDI*) times the U.S. GDP deflator (St. Louis Fed. data) divided by developing country GDP deflator (*WDI*). Changes in *x* give changes in relative PPP over time for the given country. But we need to compare values among countries, not just over time. Therefore, we assume that absolute purchasing power parity held on average over the available time period for each country *i* and compute $r_{i,t} = x_{i,t} / \bar{x}_i$. The absolute PPP assumption would be unnecessary if we could use country dummies. But there are far too many countries to specify such dummies in logit.

Exchange rate volatility = standard deviation of the four quarterly percentage changes of the developing country's U.S. dollar exchange rate within the year (*IFS*).

Real interest rate = usually the deposit rate of the host country adjusted by its GDP deflator inflation rate (*WDI*); sometimes inferred from other interest rates (*IFS*) for missing observations.

Economic size = host country GDP in 2010 U.S. dollars (*WDI*). PPP-adjusted real dollar GDP could be preferable (as used by Juhn and Mauro, 2002), but it is not available for the first half of our time period. However, a regression (using time periods where both measures are available) across all countries of the PPP-adjusted version on the non-adjusted version reveals an almost perfect linear relationship between the two ($R^2 = 0.97$). Therefore, GDP in 2010 U.S. dollars is a very good substitute.

Remoteness = distance from the world market weighted by the country's real GDP relative to world GDP, computed according to a World Bank formula (World Bank, 2014, https://openknowledge.worldbank.org/handle/10986/20522).

Time trend = the year. The trend thus has the same y intercept for every country because we do not specify country dummies. There are too many countries to specify such dummies in logit. Our specification therefore says that, given other factors, a given year has the same effect on regime choice regardless of country.

LYS exchange rate regimes: Levy-Yeyati and Sturzenegger (2005) use cluster analysis to identify *de facto* fixed, intermediate, and floating regimes based on two measures of exchange rate volatility and a measure of exchange rate reserves volatility. The intermediate regimes consist of dirty floats and crawling pegs. The fixed regimes include a "fixed inconclusive" group. The original LYS classifications run through 2000. We use the update through 2013 given in Levy-Yeyati and Sturzenegger (2016).[24]

RR exchange rate regimes: We obtain our RR regimes from Reinhart and Rogoff's (2004) *de facto* annual "coarse" regimes, of which they have are six: (1) fixed (no separate currency, pegs, currency boards, narrow bands); (2 and 3) various forms of narrow and loose crawling pegs and bands; (4) freely floating; (5) freely falling (countries and years with an annual inflation rate of 40 percent or more); (6) and dual. The first we call fixed, and the second and third we combine to call intermediate, and our third category is freely falling. The data are described in Ilzetzki, Reinhart, and Rogoff (2011) and available through 2010 from a link at http://www.carmenreinhart.com/data/browse-by-topic/topics/11/, and the link itself is http://personal.lse.ac.uk/ilzetzki/IRRBack.htm.

2. The developing countries

Below is a list of the 70 countries considered in the paper. However, because of missing data, across the 24 models of regime pairs and model specifications the full list of countries is not usually used. For the most significant individual regime pair effect, which is fix-ff for the RR reduced model

[24] We are grateful to Eduardo Levy-Yeyati for providing us an Excel file of these data.

ending in 2010, the number of countries included is 55. The omitted countries in this case are indicated in the list below with asterisks. The omitted countries in other cases are available upon request. The list:

Albania, Algeria*, Argentina, Armenia*, Bolivia, Botswana*, Brazil, Bulgaria, Cameroon, Chile*, China, Colombia*, Republic of the Congo, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Gabon, Gambia, Ghana, Guatemala, Haiti*, Honduras, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan*, Kenya, Latvia, Liberia, Lithuania, Madagascar*, Malawi, Malaysia, Mexico, Moldova*, Mongolia, Morocco, Mozambique, Nicaragua, Niger, Nigeria*, Pakistan*, Panama, Paraguay, Peru, Philippines, Poland, Romania, Russian Federation, Senegal, Slovak Republic*, South Africa*, Sri Lanka, Syrian Arab Republic*, Tanzania, Thailand, Togo, Tunisia*, Turkey, Uganda, Ukraine, Uruguay, Venezuela, Zambia, Zimbabwe

3. Descriptive statistics for FDI and other key variables

Table A1 gives the medians and 0.05 and 0.95 percentiles for several key variables: FDI as a percent of GDP (the response variable), real GDP growth (positively responding to FDI in the literature), and real GDP and trade openness (important confounders of the regime-FDI relationship in the literature). Note that a naïve interpretation would conclude that inward FDI is encouraged by relatively floating regimes. This interpretation does not control for the confounders in the table or any others.

Table A1
Descriptive statistics.

		Exchange Rate Regimes					
		LYS definitions			RR definitions		
		fixed	interm	float	fixed	interm	free fall
Attributes	**No. of regime country/year units**	681	564	672	504	1071	78
Median FDI % of GDP	0.05 percentile	-0.4	0.0	0.1	-0.1	0.0	-1.3
	0.50 percentile	**1.7**	**1.6**	**2.0**	**1.5**	**1.6**	**1.7**
	0.95 percentile	12.3	8.8	9.1	7.7	8.5	7.6
Median % real GDP growth rate	0.05 percentile	-4.5	-7.6	-1.4	-3.6	-4.0	-13.5
	0.50 percentile	**3.9**	**3.7**	**4.7**	**3.8**	**4.2**	**4.2**
	0.95 percentile	9.8	10.2	9.8	8.8	9.7	9.3
Real GDP, 2010 US $, billions	0.05 percentile	2.0	3.4	4.2	2.5	3.7	0.7
	0.50 percentile	**15.6**	**35.7**	**57.3**	**17.0**	**31.1**	**30.5**
	0.95 percentile	343.8	1000.0	951.6	410.7	619.5	812.2
Trade openness % = 100(exports + imports)/GDP	0.05 percentile	30.7	19.6	26.9	33.1	25.5	13.3
	0.50 percentile	**67.4**	**58.3**	**59.1**	**61.4**	**59.6**	**57.5**
	0.95 percentile	145.6	122.3	132.9	131.4	124.6	126.8

References

Abbott, A., Cushman, D.O., De Vita, G., 2012. Exchange rate regimes and foreign direct investment flows to developing countries. Review of International Economics, 20, 95–107.

Abbott, A., De Vita, G., 2011. Evidence on the impact of exchange rate regimes on bilateral FDI flows. Journal of Economic Studies, 38, 253–274.

Aizenman, J., 1992. Exchange Rate Flexibility, Volatility, and Domestic and Foreign Direct Investment. IMF Staff Papers, 39, 890–922.

Austin, P.C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate Behavioral Research, 46, 399–424.

Austin, P.C., Grootendorst, P., Anderson, G.M., 2007. A comparison of the ability of different propensity score models to balance measured variables between treated and untreated subjects: a Monte Carlo study. Statistics in Medicine, 26, 734–753.

Barro, R.J., Lee, J-W., 2013, A new data set of educational attainment in the world, 1950-2010. Journal of Development Economics, 104, 184-198.

Becker, S.O., Ichino, A., 2002. Estimation of average treatment effects based on propensity scores. The Stata Journal, 2, 358–377.

Bénassy-Quéré, A., Fontagné, L., Lahrèche-Révil, A., 2001. Exchange-rate strategies in the competition for attracting foreign direct investment. Journal of the Japanese and International Economies, 15, 178–198.

Bergstrand, J.H., Egger, P., 2007. A knowledge-and-physical-capital model of international trade flows, foreign direct investment, and multinational enterprises. Journal of International Economics, 73, 278-308.

Black, D.A., Smith, J.A., 2004. How robust is the evidence on the effects of the college quality? Evidence from matching. Journal of Econometrics, 121, 99–124.

Bleaney, M., Francisco, M., 2007. Exchange rate regime, inflation and growth in developing countries. The Berkeley Electronic Journal of Macroeconomics, 7. Article No. 18.

Blonigen, B., 1997. Firm-specific assets and the link between exchange rates and foreign direct investment. American Economic Review, 87, 447–465.

Blonigen, B., Piger, J., 2014. Determinants of foreign direct investment. Canadian Journal of Economics, 47, 775–812.

Bodory, H., Camponovo, L., Huber, M., Lechner, M., 2016. The finite sample performance of inference methods for propensity score matching and weighting estimators. IZA Discussion Paper No. 9706, Institute for the Study of Labor, Bonn, Germany.

Borensztein, E., De Gregorio, J., Lee, J. W., 1998. How does foreign direct investment affect economic growth? Journal of International Economics, 45, 115–135.

Bouoiyour, J., Rey, S., 2005. Exchange rate regime, real exchange rate, trade flows and foreign direct investments: the case of Morocco. African Development Review, 17, 302–334.

Broda, C., 2006. Exchange rate regimes and national price levels. Journal of International Economics, 70, 52–81.

Brookhart, M.A., Schneeweiss, S., Rothman, K.J., Glynn, R.J., Avorn, J., Stürmer, T., 2006. Variable selection for propensity score models. American Journal of Epidemiology, 163, 1149–1156.

Brüggemann, R., Lütkepohl, H., 2001. Lag selection in subset VAR models with an application to a U.S. monetary system. In: Friedmann, R., Knüppel, L., Lütkepohl, H. (Eds.), Econometric Studies: A Festschrift in Honour of Joachim Frohn. Münster, LIT Verlag, pp. 107–128.

Busse, M., Hefeker, C., Nelgen, S., 2013. Foreign direct investment and exchange rate regimes. Economics Bulletin, 33, 843–858.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22, 31–72.

Campa, M.J., 1993. Entry by foreign firms in the United States under exchange rate uncertainty. Review of Economics and Statistics, 75, 614–622.

Carr, D., Markusen, J.R., Maskus, K.E., 2001. Estimating the knowledge–capital model of the multinational enterprise. American Economic Review, 91, 693–708.

Çeviş, İ., Çamurdan, B., 2007. The economic determinants of foreign direct investment in developing countries and transition economies. The Pakistan Development Review, 46, 285–299.

Chakrabarti, R., Scholnick, B., 2002. Exchange rate expectations and FDI flows. Weltwirtschaftliches Archiv, 138, 1–21.

Chinn, M.D., Ito. H., 2006. What matters for financial development? Capital controls, institutions, and interactions. Journal of Development Economics, 81, 163–192.

Chinn, M.D., Ito, H., 2008. A new measure of financial openness. Journal of Comparative Policy Analysis, 10, 309–322.

Cushman, D.O., 1985. Real exchange rate risk, expectations, and the level of foreign direct investment. Review of Economics and Statistics, 67, 297–308.

Cushman, D.O., 1988. Exchange-rate uncertainty and foreign direct investment in the United States. Weltwirtschaftliches Archiv, 124, 322–336.

Cushman, D.O., 2016. A unit root in postwar U.S. real GDP still cannot be rejected, and yes, it matters. Econ Journal Watch, 13, 5–45.

Cushman, D.O., Michael, N., 2011. Nonlinear trends in real exchange rates: a panel unit root test approach. Journal of International Money and Finance, 30, 1619–1637.

De Menil, G., 1999. Real capital market integration: how far has integration gone? What Euro effect? Economic Policy, 14, 167–201.

De Vita, G., Abbott, A.J., 2007. Do exchange rates have any impact upon UK inward foreign direct investment? Applied Economics, 39, 2553–2564.

De Vita, G., Kyaw, K.S., 2008. Determinants of capital flows to developing countries: a structural VAR analysis. Journal of Economic Studies, 35, 304–322.

Dehejia, R.H., Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. Review of Economics and Statistics, 84, 151–161.

Deuss, A., 2012. The economic growth impacts of sugarcane expansion in Brazil: an inter-regional analysis. Journal of Agricultural Economics, 63, 528–551.

Dixit, A.K., Pindyck, R.S., 1994. Investment under Uncertainty. Princeton University Press, Princeton, NJ.

Dorn, S., Egger, P., 2013. Fixed currency regimes and the time pattern of trade effects. Economics Letters, 119, 120–123.

Dorn, S., Egger, P. 2015. On the distribution of exchange rate regime treatment effects on international trade. Journal of International Money and Finance, 53, 75–94.

Eichengreen, B., Razo-Garcia, R., 2013. How reliable are de facto exchange rate regime classifications? International Journal of Finance and Economics, 18, 216-239.

Frankel, J., Rose, A., 2002. An estimate of the effect of common currencies on trade and income. Quarterly Journal of Economics, 117, 437–466.

Froot, K., Stein, J., 1991. Exchange rates and foreign direct investment: an imperfect capital markets approach. Quarterly Journal of Economics, 106, 1191–1217.

Gnimassoun, B., 2015. The importance of the exchange rate regime in limiting current account imbalances in sub-Saharan African countries. Journal of International Money and Finance, 53, 36–74.

Goldberg, L.S., Kolstad, C., 1995. Foreign direct investment, exchange rate variability and demand uncertainty. International Economic Review, 36, 855–873.

Görg, H., Wakelin, K., 2002. The impact of exchange rate volatility on US direct investment. The Manchester School, 70, 380–397.

Greenland, S., Poole, C., 2013. Living with *P* values: resurrecting a Bayesian perspective on frequentist statistics. Epidemiology, 24, 62–68.

Heinrich, C., Maffioli A., Vázquez, G., 2010. A primer for applying propensity-score matching. Impact-Evaluation Guidelines, Technical Notes No. IDB-TN-161, Office of Strategic Planning and Development Effectiveness, Inter-American Development Bank.

Hendry, D.F., Krolzig, H-M., 2001. Automatic Econometric Model Selection Using PcGets. Timberlake Consultants, London, UK.

Ilzetzki, E.O., Reinhart, C.M., Rogoff, K., 2011. The Country Chronologies and Background Material to Exchange Rate Arrangements into the 21st Century: Will the Anchor Currency Hold? Mimeo. http://personal.lse.ac.uk/ilzetzki/data/ERA-Country_Chronologies_2011.pdf

Ioannidis, J.P.A., 2008. Why most discovered true associations are inflated. Epidemiology, 19, 640–648.

Imbens, G.W., 2000. The role of the propensity score in estimating dose–response functions. Biometrika, 87, 706–710.

Juhn, G.S., Mauro, P., 2002. Long-Run Determinants of Exchange Rate Regimes: A Simple Sensitivity Analysis. IMF Working Paper No. 02/104. International Monetary Fund, Washington, DC.

Kennedy, P., 2003. A Guide to Econometrics (5th ed.). MIT Press, Cambridge, MA.

Klein, M.W., Shambaugh, J.C., 2006. Fixed exchange rates and trade. Journal of International Economics, 70, 359–383.

Klein, M.W., Shambaugh, J.C., 2008. The dynamics of exchange rate regimes: fixes, floats, and flips. Journal of International Economics, 75, 70–90.

Krugman, P.R., Obstfeld, M., 2009. International Economics: Theory and Policy (8th ed.). Pearson, Boston, MA.

Lechner, M., 2001. Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. In: Lechner, M., Pfeiffer, F. (Eds.), Econometric Evaluation of Labour Market Policies. Physica, Heidelberg, pp. 1–18.

Levy-Yeyati, E., Sturzenegger, F., 2003. To float or to fix: evidence on the impact of exchange rate regimes on growth. American Economic Review, 93, 1173–1193.

Levy-Yeyati, E., Sturzenegger, F., 2005. Classifying exchange rate regimes: deeds vs. words. European Economic Review, 49, 1603–1635.

Levy-Yeyati, E., Sturzenegger, F., 2016. Classifying exchange rate regimes: 15 years later. Working paper No. 319, Center for International Development at Harvard University.

Li, X., Liu, X., 2005. Foreign direct investment and economic growth: an increasingly endogenous relationship. World Development, 33, 393–407.

Love, J.H., Lage-Hidalgo, F., 2000. Analysing the determinants of US direct investment in Mexico. Applied Economics, 23, 1259–1267.

Nair-Reichert, U., Weinhold, D., 2001. Causality tests for cross-country panels: a new look at FDI and economic growth in developing countries. Oxford Bulletin of Economics and Statistics, 63, 153–171.

Poulsen, L.S., Hufbauer, G.C., 2011. Foreign direct investment in times of crisis. Transnational Corporations, 20, 19–37.

Qureshi, M.S., Tsangarides, C., 2012. Hard or soft pegs? Choice of exchange rate regime and trade in Africa. World Development, 40, 667–680.

Reinhart, C.M., Rogoff, K.S., 2004. The modern history of exchange rate arrangements: a reinterpretation. Quarterly Journal of Economics, 119, 1–48.

Rogoff, K.S., Husain, A.M., Mody, A., Brooks, R., Oomes, N., 2003. Evolution and Performance of Exchange Rate Regimes. IMF Working Paper No. 03/243. International Monetary Fund, Washington/DC.

Romano, J.P., Shaikh, A.M., Wolf, M., 2010. Multiple Testing. New Palgrave Dictionary of Economics, Online Edition.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41–50.

Rubin, D.B., Thomas, N., 1996. Matching using estimated propensity score: relating theory to practice. Biometrics, 52, 249–264.

Schiavo, S., 2007. Common currencies and FDI flows. Oxford Economic Papers, 59, 536–560.

Shambaugh, J.C., 2004. The effect of fixed exchange rates on monetary policy. Quarterly Journal of Economics, 119, 300-351.

Simes, R.J., 1986. An improved Bonferroni procedure for multiple tests of significance. Biometrika, 73, 751–754.

Tavlas, G., Dellas, H., Stockman, A.C., 2008. The classification and performance of alternative exchange-rate systems. European Economic Review, 52, 941– 963.

Udomkerdmongkol, M., Morrissey, O., Görg, H., 2009. Exchange rates and outward foreign direct investment: US FDI in emerging economies. Review of Development Economics, 13, 754–764.

World Bank, 2014. Enhancing Competitiveness in an Uncertain World. East Asia and Pacific Economic Update, October.

Yang, J.Y.Y., Groenewold, N., Tcha, M., 2000. The determinants of foreign direct investment in Australia. Economic Record, 76, 45–54.

Supplementary file for "Exchange rate regimes and FDI in developing countries: a propensity score matching approach"

Details of PSM estimates

The tables below come in sets of three. Each set concerns one the methods of regime definition and the full model or the reduced model with larger sample size. Each table in a set gives results for one of the three pairs of exchange rate regimes to be compared. Each table first shows the total number of country/year units available after missing observations are dropped, or after variables are dropped and the sample size increased. The number of country/year units for each regime in the pair is also given. The table is then divided into two parts, one for each regime as treatment. The rows of this section give various results for the four ways of computing the ATT with each regime as the treatment, with column definitions as follows:

total obs., fix, float, int, f. fall = total number of observations (regimes), and breakdown of fixed, floating, intermediate, and freely falling regimes, prior to imposition of the common support option and matching.

tr = number of treated units used to compute the ATT.

co = number of matched control units used to compute the ATT.

ATT = average treatment effect on the treated.

t-stat-a = analytical *t*-statistic, when available (space left blank if not).

t-stat-b = bootstrapped *t*-statistic.

p-value = Simes p-value using **t-stat-a** and **t-stat-b**.

Table S1
LYS full models through 2013.

(a) Fixed and floating regimes

	total obs. = 742			fix = 307		float = 435						
	treatment = fix						treatment = float					
	tr	co	ATT	t-stat-a	t-stat-b	p-value	tr	co	ATT	t-stat-a	t-stat-b	p-value
ATTk	307	416	0.17		0.32	0.75	435	195	-0.56		-1.36	0.18
ATTnd	307	78	-0.03	-0.02	-0.03	0.99	435	70	-0.50	-0.48	-1.26	0.42
ATTr	307	416	0.51	1.28	1.43	0.20	435	195	-0.39	-0.67	-1.12	0.50
ATTs	307	416	-0.08	-0.12	-0.12	0.90	435	195	-0.46	-1.08	-1.05	0.30

(b) Intermediate and floating regimes

	total obs. = 728			int = 293		float = 435						
	treatment = intermediate						treatment = float					
	tr	co	ATT	t-stat-a	t-stat-b	p-value	tr	co	ATT	t-stat-a	t-stat-b	p-value
ATTk	293	435	-0.30		-0.88	0.38	435	282	0.29		1.25	0.21
ATTnd	293	144	-0.77	-1.39	-1.64	0.17	435	149	0.32	0.96	1.13	0.34
ATTr	288	435	0.07	0.31	0.29	0.77	435	282	0.22	0.91	0.98	0.36
ATTs	290	435	-0.45	-1.04	-1.04	0.30	435	282	0.28		1.16	0.25

(c) Fixed and intermediate regimes

	total obs. = 600			fix = 307		int = 293						
	treatment = fix						treatment = intermediate					
	tr	co	ATT	t-stat-a	t-stat-b	p-value	tr	co	ATT	t-stat-a	t-stat-b	p-value
ATTk	307	280	0.34		0.67	0.51	293	286	-0.47		-1.00	0.32
ATTnd	307	89	1.17	1.81	2.58	***0.020***	293	92	-0.79	-1.24	-1.20	0.23
ATTr	307	280	0.36	1.00	0.92	0.36	293	286	-0.49	-1.09	-1.35	0.28
ATTs	306	280	0.62	0.98	0.98	0.33	293	286	-0.35	-0.75	-0.75	0.46

Table S2
LYS reduced models through 2013.

(a) Fixed and floating regimes

			total obs. = 1039			**fix =** 471		**float =** 568				
	treatment = fix						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	471	551	-0.08		-0.18	0.86	568	376	-0.77		-1.38	0.17
ATTnd	471	98	0.34	0.26	0.61	0.80	568	102	-1.04	-1.18	-1.70	0.18
ATTr	471	551	0.00	0.01	0.01	0.99	568	376	-0.62	-1.37	-1.55	0.17
ATTs	471	551	0.21	0.47	0.47	0.64	568	376	-0.82	-1.46	-1.46	0.15

(b) Intermediate and floating regimes

			total obs. = 1042			**int =** 458		**float =** 584				
	treatment = intermediate						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	458	581	-0.39		-0.70	0.48	584	458	0.36		1.21	0.23
ATTnd	458	252	0.06	0.09	0.12	0.93	584	258	0.27	0.64	0.79	0.52
ATTr	458	581	-0.37	-0.98	-0.84	0.40	584	458	0.33	0.83	1.12	0.41
ATTs	458	581	-0.25	-0.52	-0.52	0.60	583	459	0.39		1.31	0.19

(c) Fixed and intermediate regimes

			total obs. = 948			**fix =** 530		**int =** 418				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	530	406	-0.63		-0.77	0.44	418	516	-0.29		-0.50	0.62
ATTnd	530	134	-0.32	-0.18	-0.61	0.86	418	132	-0.88	-1.04	-1.07	0.30
ATTr	530	406	-0.56	-1.05	-0.88	0.38	418	516	0.01	0.03	0.03	0.98
ATTs	530	406	0.32	0.71	0.71	0.48	418	516	-0.32	-0.52	-0.53	0.60

Table S3
LYS full models through 2007.

(a) Fixed and floating regimes

			total obs. = 542		fix = 229		float = 313					
	treatment = fix						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	229	215	-0.53		0.89	0.38	313	301	-1.26		-2.55	***0.011***
ATTnd	229	55	0.06	0.07	0.07	0.94	313	57	-1.25	-1.22	-2.26	***0.049***
ATTr	229	215	0.02	0.05	0.04	0.97	313	301	-0.98	-1.69	-2.57	***0.021***
ATTs	229	215	-0.76	-1.05	-1.01	0.31	313	301	-1.34	-2.66	-2.64	***0.008***

(b) Intermediate and floating regimes

			total obs. = 538		int = 225		float = 313					
	treatment = intermediate						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	225	306	-0.11		-0.40	0.69	313	216	0.23		1.09	0.28
ATTnd	225	117	0.03	0.10	0.10	0.92	313	115	0.32	1.05	1.26	0.30
ATTr	220	306	0.30	1.31	1.32	0.19	313	216	0.06	0.25	0.30	0.80
ATTs	222	306	0.02	0.09	0.09	0.93	313	216	0.27		1.20	0.23

(c) Fixed and intermediate regimes

			total obs. = 454		fix = 229		int = 225					
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	229	214	-0.05		-0.12	0.91	225	223	-0.75		-1.48	0.14
ATTnd	229	77	0.19	0.34	0.42	0.73	225	72	-0.92	-1.26	-1.84	0.13
ATTr	229	214	-0.02	-0.06	-0.06	0.95	225	223	-0.59	-1.44	-1.41	0.16
ATTs	228	214	0.13	0.29	0.29	0.78	223	225	-0.64	-1.56	-1.57	0.12

Table S4
LYS reduced models through 2007.

(a) Fixed and floating regimes

			total obs. = 802			**fix =** 389		**float =** 413				
	treatment = fix						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	389	394	-0.62		1.37	0.17	413	339	-0.81		-1.86	0.064
ATTnd	389	82	-0.05	-0.08	-0.08	0.94	413	84	-1.23	-1.96	-2.64	***0.017***
ATTr	389	394	-0.36	-1.21	-1.06	0.29	413	339	-0.54	-1.53	-1.85	0.13
ATTs	389	394	-0.47	-1.19	-1.19	0.24	413	339	-0.81	-1.86	-1.84	0.066

(b) Intermediate and floating regimes

			total obs. = 800			**int =** 369		**float =** 431				
	treatment = intermediate						**treatment = float**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	369	425	-0.17		-0.82	0.41	431	366	0.01		0.04	0.97
ATTnd	369	172	-0.01	-0.04	-0.04	0.97	431	175	-0.13	-0.47	-0.53	0.64
ATTr	369	425	-0.16	-0.87	-0.82	0.42	431	366	0.00	0.02	0.02	0.98
ATTs	366	428	-0.06	-0.32	-0.31	0.76	428	369	0.04	0.21	0.21	0.84

(c) Fixed and intermediate regimes

			total obs. = 929			**fix =** 514		**int =** 415				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	514	408	-0.64		-0.83	0.41	415	510	0.05		0.11	0.91
ATTnd	514	143	-0.25	-0.35	-0.30	0.77	415	140	-0.10	-0.12	-0.22	0.90
ATTr	514	408	-0.35	-0.61	-0.59	0.56	415	510	0.14	0.26	0.36	0.79
ATTs	514	408	-0.74	-0.90	-0.90	0.37	415	510	0.06	0.16	0.15	0.88

Table S5
RR full models through 2010.

(a) Fixed and freely falling regimes

			total obs. = 316			**fix =** 249		**ff =** 67				
	treatment = fix						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	249	13	1.68		1.58	0.12	67	66	-1.14		-1.12	0.26
ATTnd	249	9	0.76	0.39	0.63	0.70	67	9	-1.15	-0.83	-1.11	0.41
ATTr	248	12	1.83	1.28	1.97	0.101	18	66	0.34	0.60	0.43	0.67
ATTs	249	13	1.69	1.67	1.67	0.096	64	66	-1.04	-1.22	-1.22	0.23

(b) Intermediate and freely falling regimes

			total obs. = 722			**int =** 655		**ff =** 67				
	treatment = intermediate						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	655	60	0.65		0.74	0.46	67	297	-0.71		-0.59	0.56
ATTnd	655	25	1.59	1.25	2.12	0.069	67	24	-1.24	-1.14	-0.86	0.39
ATTr	655	60	0.62	1.04	0.73	0.46	67	297	-0.74	-3.02	-2.14	***0.005***
ATTs	654	60	0.62	0.71	0.74	0.48	62	297	-1.10		-0.79	0.53

(c) Fixed and intermediate regimes

			total obs. = 904			**fix =** 249		**int =** 655				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	249	625	1.12		1.56	0.12	655	228	-0.28		-0.43	0.67
ATTnd	249	33	1.30	1.35	1.58	0.18	655	33	0.30	0.24	0.55	0.81
ATTr	246	625	0.73	2.19	2.19	***0.029***	655	225	-0.29	-0.35	-0.50	0.73
ATTs	245	628	1.19	1.81	1.81	0.071	655	228	-0.19	-0.30	-0.30	0.76

Table S6
RR reduced models through 2010.

(a) Fixed and freely falling regimes

			total obs. = 518			**fix =** 397		**ff =** 121				
	treatment = fix						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	397	117	1.71		2.16	***0.031***	121	159	-0.72		-0.83	0.41
ATTnd	397	18	0.70	0.77	0.63	0.53	121	19	-0.13	-0.16	-0.15	0.88
ATTr	395	117	2.06	3.41	3.38	***0.001***	121	157	-0.81	-0.97	-1.15	0.33
ATTs	397	117	1.31	1.24	1.24	0.22	121	159	-1.17	-1.17	-1.17	0.24

(b) Intermediate and freely falling regimes

			total obs. = 822			**int =** 737		**ff =** 85				
	treatment = intermediate						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	737	77	0.92		1.30	0.19	85	582	-0.14		-0.32	0.75
ATTnd	737	35	1.63	1.41	1.90	0.12	85	34	0.08	0.19	0.16	0.87
ATTr	737	77	0.94	1.57	1.39	0.17	85	582	-0.80	-3.29	-2.30	***0.002***
ATTs	737	77	0.88	1.11	1.08	0.28	82	582	-0.25		-0.52	0.60

(c) Fixed and intermediate regimes

			total obs. = 1319			**fix =** 407		**int =** 912				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	407	822	0.94		1.62	0.105	912	384	-0.11		-0.22	0.83
ATTnd	407	44	1.00	1.68	1.39	0.17	912	44	-0.26	-0.45	-0.38	0.71
ATTr	407	822	0.46	1.45	1.55	0.15	912	384	-0.09	-0.12	-0.21	0.90
ATTs	405	824	0.79	1.39	1.39	0.16	911	385	-0.15	-0.28	-0.28	0.78

Table S7
RR full models through 2007.

(a) Fixed and freely falling regimes

			total obs. = 265			**fix =** 198		**ff =** 67				
	treatment = fix						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	198	13	1.28		1.25	0.21	67	60	-1.16		-1.11	0.27
ATTnd	198	8	0.50	0.26	0.42	0.79	67	8	-1.10	-1.03	-1.06	0.30
ATTr	198	13	1.45	1.08	1.50	0.27	16	60	0.19	0.32	0.22	0.82
ATTs	198	13	1.26	1.20	1.20	0.23	64	60	-1.00	-1.06	-1.06	0.29

(b) Intermediate and freely falling regimes

			total obs. = 625			**int =** 558		**ff =** 67				
	treatment = intermediate						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	558	60	0.48		0.58	0.56	67	285	-0.63		-0.53	0.60
ATTnd	558	24	1.22	1.09	1.58	0.23	67	22	-1.53	-1.45	-1.05	0.30
ATTr	558	60	0.46	0.78	0.54	0.59	67	285	-0.71	-2.90	-2.14	***0.008***
ATTs	557	60	0.46	0.53	0.54	0.59	62	285	-1.12		-0.79	0.54

(c) Fixed and intermediate regimes

			total obs. = 756			**fix =** 198		**int =** 558				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	198	436	0.68		0.88	0.38	558	148	-0.58		-0.72	0.47
ATTnd	198	27	1.16	1.06	1.00	0.32	558	27	-0.99	-1.08	-1.16	0.28
ATTr	195	436	0.45	1.19	1.17	0.24	558	145	-0.48	-0.62	-0.68	0.53
ATTs	185	448	0.76	0.91	0.91	0.36	558	148	-0.60	-0.77	-0.77	0.44

Table S7
RR reduced models through 2007.

(a) Fixed and freely falling regimes

			total obs. = 589			**fix =** 408		**ff =** 181				
	treatment = fix						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	408	180	0.31		0.33	0.74	181	202	-0.63		-1.08	0.28
ATTnd	408	22	-0.88	-0.88	-0.67	0.50	181	23	-0.69	-0.83	-1.11	0.41
ATTr	408	180	0.88	2.04	1.31	0.084	181	202	-0.63	-0.69	-1.58	0.23
ATTs	408	180	-0.07	-0.07	-0.07	0.95	181	202	-0.85	-1.23	-1.12	0.26

(b) Intermediate and freely falling regimes

			total obs. = 714			**int =** 629		**ff =** 85				
	treatment = intermediate						**treatment = ff**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	629	77	0.72		1.06	0.29	85	529	-0.13		-0.31	0.76
ATTnd	629	35	1.41	1.34	1.79	0.15	85	34	0.07	0.16	0.13	0.89
ATTr	629	77	0.83	1.41	1.28	0.20	85	529	-0.65	-2.69	-2.10	***0.015***
ATTs	629	77	0.81	1.14	1.14	0.26	82	529	-0.23	-0.53	-0.51	0.61

(c) Fixed and intermediate regimes

			total obs. = 1287			**fix =** 410		**int =** 877				
	treatment = fix						**treatment = intermediate**					
	tr	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**	**tr**	**co**	**ATT**	**t-stat-a**	**t-stat-b**	**p-value**
ATTk	410	830	0.40		0.58	0.56	877	318	-0.69		-1.00	0.32
ATTnd	410	41	0.61	0.74	0.79	0.46	877	42	0.00	0.00	0.01	1.00
ATTr	410	830	0.24	0.77	0.72	0.47	877	318	-0.28	-0.38	-0.57	0.70
ATTs	408	832	0.50	0.76	0.76	0.45	876	319	-0.70	-1.04	-1.04	0.30