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Herding in Aid Allocation

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I. INTRODUCTION

The literature in economics on foreign aid has extensively explored the issue of aid efficiency, attempting to answer the key question of whether aid indeed promotes growth. After many articles evaluating the effect of aid on growth (see Roodman 2007 for a recent review of the literature) often reaching somewhat disappointing conclusions, some have started to narrow the question and look at the effect of aid on more specific variables (for instance Mishra and Newhouse 2007 on the effect of aid on infant mortality). Nevertheless, the question still remains firmly focused on the effect of aid on a given growth outcome. Another fertile strand of the literature focuses on aid allocation determinants (see, among many others, Alesina and Weder 2002, and Berthélémy 2006). However how one donor's decisions may affect others' allocations is still little understood. This is not a completely new concern. Cassen (1986) already mentioned that donors moved in herds, suddenly disbursing money into "star" countries, and that sudden increases were followed by long aid declines. While this claim has been made (Riddell 2007 argues that there is a "herd instinct" among donors), no study has yet attempted to measure herding and to determine its causes.

This article is a first step in this direction. While herding is now a basic assumption among traders in bonds and equities, much less is known about aid donors. However if the latter also herd, might not such behaviour from both public and private actors compound to create even greater overall herding? Because aid donors are somehow expected to play a different role to that of

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private investment, we believe it is relevant to compare these different actors' actual behaviour.[1]

The concept of herding was originally developed by sociologists following the seminal work of French social scientist Gustave Le Bon, who published his famous *La psychologie des foules* in 1895 and some years later by George Simmel in another seminal book published in 1903, *The Metropolis and Mental Life*. The very first economist to refer to this notion was Thorstein Veblen; in his 1899 essay *The Theory of the Leisure Class*, he explained economic behaviour in terms of social influences such as "emulation", where some members of a group mimic other members of higher status. The notion has grown to become used extensively by financial economists over the past decades. Bikhchandani and Sharma (2000), or Hirshleifer and Teoh (2003), provide overviews of the field. The academic study of behavioral finance has identified herding as an important factor in the collective irrationality of investors, particularly the work of Robert Shiller (2000).

This article offers different measures of herding to test for its presence in aid allocation and evaluate its size. Our results all reject the hypothesis of no herding, with its importance depending on the chosen measure. We develop two indexes directly inspired by the financial literature. The first one is the most widely used in the finance literature. It was proposed by Lakonishok et al. (1992) and has subsequently been broadly applied in the field. It is based on the simple intuition that there is herding when many more traders (donors) buy or sell a stock (increase or decrease aid to a recipient) than they do on average. The variable on which the herding measure is based is therefore the proportion of traders (donors) buying (increasing aid to) each stock-quarter (recipient-year). Frey et al. (2007) recently showed that this measure was negatively biased and did not consistently estimate herding even for large sample sizes. They proposed an alternative consistent measure based on the same intuition but relying on a simple structural model, which we also apply here.

Nevertheless, these measures are used in this article with some variations from the finance literature to capture the specificity of aid allocation. Their application to this field raises a number of issues that we address. First, we present results using two types of data frequency. Yearly data is available for aid allocation, but is likely to be contaminated by small, "noisy", aid movements and may fail to capture the actual donor allocation horizon. In addition to yearly data, 3 and 5-year allocations are used to account for inertia in aid allocation and eliminate some noise. Second, herding measures also capture co-movements from donor countries that are due to clearly identifiable causes. A country may for instance be at war, and donors may be reluctant to spend

1. For a comparison between aid donors and portfolio funds regarding quantities, volatility and fragmentation, see Frot and Santiso (2008).

money during wars, lest they indirectly finance the conflict. More democratic institutions may also prompt a swift increase in aid flows from most donors. These simultaneous decisions appear as herding –many donors taking the same decision at the same time, when they only are the consequences of similar allocation rules. Such events inflate herding measures, to the point that they become difficult to interpret. For this reason, we estimate a corrected herding measure that removes the contributions of these observable factors.[2]

Our preferred measure uses 3-year data and suggests that herding size is around 10 per cent, using the Frey et al. (2007) index, or around 3 percent using the more conventional Lakonishok et al. (1992) index. Using the first estimation, it implies that in a world where 50 per cent of all allocation changes are increases, the average recipient experiences 60 per cent of its donors changing their allocation in the same direction. In other words half of the recipients see 60 per cent of their donors increase their allocations, and the other half sees a 60 per cent decrease their aid allocations. Our lower bound for herding size, based on measures using yearly data, is around 6 per cent.

To address the issue of common observable factors affecting donor allocation rules, herding determinants are estimated to better understand what enters into our measures, and the effects of various shocks are evaluated using appropriate generalized linear model (GLM) techniques. Predictably, we find that transitions towards less democratic regimes cause donors to simultaneously decrease aid allocations. However, the opposite does not reveal itself to be the case. This asymmetry, while somewhat puzzling, is robust to all our specifications. Natural disasters, unsurprisingly, also create herding, wars, however, do not. This estimation in itself may contribute to the debate on the determinants of aid, suggesting which factors trigger responses from donors, positive or negative. If we consider that donors first choose which recipients should receive more aid than in previous years and then, given a fixed aid budget, subsequently decide on precise allocation numbers then our results provide empirical estimates of the first step of the process.

Importantly, GLM estimates allow us to calculate the contribution of each determinant to the herding measure, and so to compute a herding measure free of the effects of these determinants. Those in fact explain little of herding, which cannot be solely attributed to political factors, natural disasters or wars. Though we must be careful in interpreting this result, it suggests that other non-observable factors are at play, and in particular factors that relate directly to "pure" herding such as information cascades or signalling.

2. In the working paper version of the paper, Frot and Santiso (2009), an additional contribution, and deviation from the finance literature, is to present a herding measure that discards cross country variation and is based on deviations from past decisions within each country. We focus here on a single measure, following the finance literature.

Our motivations for studying herding are twofold. First, herding imposes costs and benefits on recipients. It can be regarded positively as the coordination of donors in cases of emergency. Humanitarian needs following a natural disaster or a war naturally call for a greater aid effort from donors. This article attempts to avoid including such "beneficial" herding in its measures by carefully defining aid.

On the other hand herding is usually associated with sudden swings and an overflow of money that is not always beneficial. In the case of aid, multiple donors implementing many missions in an uncoordinated fashion, or aid fragmentation, has been shown to decrease aid efficiency and may impose an unnecessary burden on already weak administrations in developing countries (see Djankov et al. 2009; OECD 2008; Knack and Rahman 2007). By focusing on the proportion of donors increasing aid allocations, and not on actual aid quantities, we also hope to contribute to the debate on the causes of aid fragmentation. Cassen (1986) provides an example of herding leading to fragmentation and a misallocation of resources. He mentions that a large number of donors became involved in the Kenyan rural water supply sector, resulting in an overflow of administrative procedures that the weak Kenyan Ministry of Water Development could not face. Both donors and the Kenyan Government agree that aid to this sector has been a disaster.

The costs of herding also include increased aid volatility. Herding may be an important factor behind the large swings in the levels of aid experienced by recipients, beyond the conscious coordination of aid decisions. Aid volatility has been a major concern for many years (see Bulíř and Hamann 2006) and its costs have been evaluated to be potentially very high for aid recipients (Arellano et al. 2009). While Frot and Santiso (2008) showed that other types of private capital inflows were more volatile, volatility in foreign aid flows is considered harmful for developing countries, and in particular in low income countries that are aid dependent. An unstable source of finance prevents governments from planning ahead and, as shown by Agénor and Aizenman (2007), may bring aid recipients to fall into a poverty trap by making it impossible to invest in projects requiring a steady flow of funds. Bulíř and Hamann (2006) report that aid volatility has worsened in recent years. Kharas (2008) also finds the cost of volatility to be large and argues that herd behaviour, by creating donor darlings and orphans, accentuates collective volatility, underlining that while a donor can reduce volatility by running counter the overall aid cycle, the herding phenomenon will render this unlikely.

A second motivation of the article is to improve our understanding of donor allocation policies. It has been argued that aid depends on many economic, political and historical determinants. However, the interaction between members of the donor community has been little studied. Given the very large number of actors,[3] we expect decisions to depend on various signals (recipient needs, past relationship between donor and recipient, but also other donors' decisions). While we are not the first to empirically investigate this link between donors, to our knowledge this article is the first to use herding measures to document it. Past studies have estimated the effect of total donors' aggregated aid on the aid of a specific, individual donor.

Tezanos Vázquez (2008), using this methodology, finds a "bandwagon effect" of Spanish aid. Berthélemy (2006), Berthélemy and Tichit (2004) and Tarp et al. (1998) use exactly the same approach. It is however quite different from ours, in that it does not look at simultaneous identical decisions from donors. It does not treat donors equally, as the total aid allocated to a recipient often depends on the decisions of a handful of large donors. Finally because of the reflection problem defined by Manski (1993) this effect is not consistently estimated using regressions.

Finally, herding is potentially a force contributing to the emergence of donor darlings and aid orphans. Though her study is based on NGOs rather than on official donors, Reinhardt (2006) provides some evidence that donors do herd. She reports donor agents as saying that "we know other foundations trust Organization X, so we went straight there and told them we wanted a partnership". An NGO financial director also acknowledges that "I can't get IDB money if I drop the ball with the World Bank". When repeated this behaviour creates inequalities among aid recipients even if ex ante they share similar characteristics. Marysse et al. (2006) argue that political considerations and donor coordination problems have created such donor darlings and aid orphans in the region of the Great Lakes in Africa. These two studies document micro evidence of herding, but are suggestive that a macro effect is likely to be present.

II. BEYOND FADS AND FASHIONS: BENEFICIAL HERDING

Any herding measure based on the detection of simultaneous and identical donor decisions must capture aid movements caused by exogenous factors. For instance when a natural disaster hits a country, there is indeed herding. When donors finance urgent humanitarian needs and decide simultaneously to increase their aid allocations to the country, we term this "beneficial" herding. It simply reflects suddenly increased needs that are taken into account by the donor community as a whole. It is herding in reaction to a clear, identifiable,

3. 53 donors reported their activities to the Development Assistance Committee of the OECD in 2007, but these do not include some other important donors (Brazil, China, Venezuela, etc.) and non-official donors (NGOs, private foundations and charities).

exogenous shock. The Asian Tsunami in December 2004 quickly created such beneficial herding, and other cases are easily found: Bosnia-Herzegovina and Timor-Leste faced humanitarian crises and severe reconstruction needs that triggered simultaneous aid flows from most donors. More recently, in 2008, Georgia received a USD 4.5 billion dollar aid pledge by 38 countries and 15 multilateral organisations. Donors also coordinate their actions when they grant debt relief. Many donors tremendously increased aid to Nigeria in 2005 and 2006, though this was through debt forgiveness mechanisms.

Ideally a measure of herding would distinguish between such coordinated moves, sometimes decided in international summits, and herding caused by allocation policies, strategic motives, and competition among donors. A suitable definition of aid allows the elimination of a fair share of the former. Country Programmable Aid (CPA) does not include items that are not predictable by nature: humanitarian aid, debt relief and food aid. This variable has been used recently to study aid fragmentation (OECD 2008) and trends in foreign aid (Kharas 2007). It is calculated by subtracting humanitarian aid, gross debt relief and food aid from gross aid, as defined by the Development Assistance Committee (DAC). This quantity constitutes the core of aid that finances development in a medium to long term perspective. Though not perfect, a herding measure based on this variable is not subject to the sudden aid swings due to humanitarian emergency and debt relief.

III. HERDING MEASURES

1. Definitions

Evaluating herding in aid allocation is a thorny issue, leading us to turn to the financial literature where herding has been measured and modelled for many years. Lakonishok et al. (1992) developed an index based on the idea that herding occurs when traders (donors) deviate from an "average" behaviour. Their methodology is purely statistical and does not rely on any structural model. It is therefore quite simple and general, but may not be powerful enough to detect and evaluate herding correctly. Their index LSV_{it} is defined as follows

$$LSV_{it} = |p_{it} - \pi_t| - E|p_{it} - \pi_t| \tag{1}$$

On financial markets p_{it} is the proportion of funds buying stock i in period t. By analogy in our aid study it is the proportion of donors increasing their allocation to recipient i in period t. The basic idea of the measure is that when there is no herding, aid increases and decreases are randomly distributed.

If there are an excessive number of increases or decreases then it is interpreted as herding behaviour. π_t provides the benchmark against which herding is assessed. It is the average proportion of aid increases in all the decisions taken in year t, $\pi_t = \frac{\Sigma_i b_{it}}{\Sigma_i n_{it}}$ where b_{it} is the number of aid increases and n_{it} is the number of donors active in recipient i in year t. It is the probability that a donor increases its aid to a recipient in year t under the hypothesis of no herding. The first term of the equation is positive even when there is no herding. The second term is an adjustment factor that serves as a correction. LSV_{it} has therefore a zero expected value under the hypothesis of no herding. Herding is measured by averaging LSV_{it} for the desired time period and groups of recipients and we denote this average LSV. This measure has been used by Lakonishok et al. (1992), Grinblatt et al. (1995), and Wermers (1999), amongst others, to estimate herding in mutual funds. Uchida and Nakagawa (2007) applied it to the Japanese loan market, Weiner (2006) to the oil market, and Welch (2000) to financial analysts.

The key intuition behind LSV_{it} is the dispersion of increases and decreases around the average proportion π_t. This feature makes it neutral with respect to global trends in aid allocation. If donors cut their aid budgets, as they did in the nineties, this is captured by π_t and it does not affect the herding measure. The overall increasing trend in aid over the last 50 years does not influence it either. LSV_{it} is also independent of aid concentration at the recipient level. Whether a very small number of donors represent most of the receipts, or whether all donors disburse similar quantities to a recipient does not matter. Herding is here based on the idea of similar decisions, regardless of the quantities involved. For this reason it is also detached from fixed allocation determinants due to historical ties or political economy factors. For example, the fact that a donor favours a particular recipient because it is a former colony is irrelevant here. What matters is the variation in aid from one period to the next, and not the exact quantity allocated each year.

Recently Frey et al. (2007) have shown that this approach may actually fail to measure herding properly. They develop a simple structural model to match the use and interpretation of LSV_{it} and find in simulations that the measure underestimates the true herding parameter. The adjustment factor overcorrects the estimated parameter unless there are a very high number of observations per recipient year. Unfortunately this is not the case in aid where the number of donors never exceeds 53 in our data. Frey et al. (2007) propose an alternative measure H_{it} not subject to the inherent bias of LSV_{it}:

$$H_{it} = \frac{n_{it}^2(p_{it} - \pi_t)^2 - n_{it}\pi_t(1 - \pi_t)}{n_{it}(1 - n_{it})} \tag{2}$$

n_{it} is the number of donors giving aid to recipient i in year t. H_{it} is then averaged over recipient-years. For a set A of recipient-years they define

$$H = \frac{1}{A} \sum_{(i,t) \in A} H_{it} \tag{3}$$

$$h = \sqrt{H} \tag{4}$$

h is a consistent estimator of their herding parameter. Using Monte Carlo simulations they find that LSV is a good statistic to test for the presence of herding: if LSV is significantly different from zero, then there is herding. However LSV does a poor job at estimating the *size* of herding. H is also a viable statistic to test the presence of herding and h provides an accurate estimate of herding. In particular it improves significantly with the number of recipient-years, while LSV does not. Since our sample contains at most 5171 observations h is expected to perform particularly well. Frey et al. (2007) therefore suggest a two step approach: first, test the existence of herd behaviour using either LSV or H; second if significant herding is found, estimate its level consistently using h.

Our approach follows their suggestion. For each set of recipient-years where herding is measured, LSV is reported. If the hypothesis of no herding is rejected then h is calculated to estimate its size. This approach is not flawless though. It was mentioned above that unlike LSV, h relies on a structural model. It is simple and quite general but it may not be suited to aid allocation or may miss some important characteristics. In that case h may not be a good measure.

2. *Which recipient-years? Which donors?*

The OECD DAC dataset contains 5837 recipient-years where at least one donor is active.[4] Aid activities of 60 donors are reported, though no more than 53 are ever present simultaneously. Herding measures can theoretically be based on all these observations. However there are good reasons to restrict the set of donors and recipients.

Donors enter and exit the aid market. Some donors did not give any aid before a particular year and some stopped. The fact that a new donor can only *increase* its aid allocations is not necessarily an issue because the first year a donor is present is by construction not used in the herding measure. Only second year allocations onwards are valid for our purpose since to define aid

4. A donor is defined as active in recipient i in year t if it changes its allocation to recipient i from year $t-1$ to year t.

increases and decreases in year t we need allocations in year $t-1$. On the other hand a donor that exits can only *decrease* its allocations. It may do so gradually over time if it has planned to cease its activity. Its behaviour is biased and may hide or exaggerate herding. We consequently compute our herding measure excluding donors that cease their activity.

A similar issue arises with recipients. Some countries do not "exist" before a certain date. That mainly concerns ex-Soviet Republics and regions of former Yugoslavia. There was beneficial herding towards these countries. Their geographic proximity to many important donors and their needs created an influx of aid.[5] This type of herding is conspicuous and it is large. It inflates any herding measure. Because we do not want our results to rely on these few particular cases we simply exclude them. Other entries are due to late additions to the OECD DAC recipient list. These are also excluded from the set of recipient-years. This choice is also quite restrictive as it leaves aside observations where there may be herding.[6]

Finally to talk about herding when there is only one donor does not make much sense. There must be a herd to follow in order to have herd behaviour. Recipient-years with fewer than five active donors are not considered. These restrictions leave us with a dataset that contains at most 5171 recipient-years.

LSV_{it} and H_{it} are computed for different groups of donors. Activities either from all donors are considered, or only from bilateral donors, or only from multilateral donors. Indeed one might think that bilateral donors herd but that multilateral donors take independent decisions. In that case the latter are merely adding some noise that makes herding more difficult to detect.

IV. RESULTS

Table 1 presents herding measures for different groups of donors. Herding is significant (at the 1 percent level) in all groups except among multilateral donors. Those do not herd.[7] Bilateral donors on the other hand, do. Having passed the existence test, h is computed to find herding levels.

Both LSV and h have the same interpretation. Paraphrasing Lakonishok et al. (1992), a measure of x implies that if π, the average fraction of changes that are increases, was 0.5, then $50+x$ percent of the donors were changing their allocations to an average recipient in one direction and $50-x$ percent in the

5. It is debatable whether there was herding given their characteristics: other countries under similar conditions might not have enjoyed similar attention.
6. In Frot and Santiso (2009), we tried different sets of donors and recipients, and obtained very similar results. We exclude these results here for the sake of brevity.
7. It must be clear that multilaterals do not herd among themselves. It does not imply that some of them do not herd with bilateral donors.

Table 1

Average Herding, *LSV* and *h* Measures, Yearly Data, by Donor Category

All donors		Bilateral donors		Multilateral donors	
LSV	*h*	*LSV*	*h*	*LSV*	*h*
1.07 (5171)	6.27	1.05 (4866)	6.53	0.43 (3998)	4.36

Source: Authors based on OECD data. Number of observations in parentheses.

opposite direction. As emphasised by Frey et al. (2007) *LSV* underestimates herding and is always much smaller than *h*. According to the *LSV* measure, there is statistically significant herding but not economically. Only about 1 per cent of the changes can be attributed to herding. The adjustment factor overcorrects *LSV* to the point that it cannot distinguish between randomness and herding. *h* does not suffer from the same bias. Its size implies that if the average fraction of changes that are increases is 0.5, on average around 56 percent of donors take similar decisions in a recipient-year.

Herding on financial markets using the *LSV* measure is usually higher. Lakonishok et al. (1992) find a value of 2.7, Wermers (1999) of 3.40. Herding in aid allocation would be roughly a third of what is observed in finance according to this measure.

V. ALTERNATIVE MEASURES

LSV uses yearly data to detect herding. It makes sense because donor disbursements are allocated on a yearly basis and these are expected to be influenced by herding. On the other hand, donors, unlike traders, commit to future disbursements over several years. Many projects have a longer horizon than a year. Even if they herd, donors might find it difficult to stop programs currently running and shifts in allocation may take some years before taking effect. Year-on-year changes may fail to capture such movements and on the contrary be oversensitive to small variations that do not reflect herding but rather marginal changes due to project progression. Indeed many aid changes are quite small: the median absolute change for all donors is USD 0.80 million but the average is 8.53 million. The distribution of changes is strongly skewed towards small values. It is difficult to argue that such small variations always reflect donor choices. However *LSV* (or *h*) treat changes regardless of their sizes. These limited variations may inflate herding measures artificially by putting some weight on random variations. They also create noise in the data that makes herding more difficult to detect.

We propose to smooth random variations away by using 3-year periods. Instead of using year-on-year changes, disbursements are added up over a period of three years and a donor is said to increase its aid to a recipient between two periods if its disbursements over three years are higher than over the three precedent years (here again a period is valid only if the donor disbursed aid during each of the three years of the period). Collapsing the data in such a way drastically reduces the number of observations but increases the median size of an absolute change from 1.52 to 4.87 million. Lengthening the period takes into account the medium term perspective of development aid. The exact length is arbitrary, and results using 5-year periods are also presented.

The first two columns use three-year periods to detect herding. Its presence is confirmed and its size is above what has been found in Table 1 (all the reported coefficients are significantly different from zero at the 1 percent level). *h* measured on yearly data yielded a value of 6.27. 3-year data reveal a herding level of 11.20. 5-year data provide a similar and even stronger conclusion. Results are even stronger with the *LSV* measure whose size is multiplied by three. Magnitudes are now similar to those observed on financial markets. If we are willing to adopt a slightly longer term perspective, herding appears to be more pronounced. Given the way aid is disbursed with commitments and tranche disbursements as projects progress, this perspective seems well suited and avoids building measures on often small yearly variations.

Table 2 confirms that there is significant herding in aid allocation and that its size is actually more important than what is derived from yearly data. Longer periods yield levels above or similar to what has been measured on financial markets with quarterly data. A high frequency makes sense in finance where investors are quick to respond and modify their portfolio choices, but much less in development. It is difficult to identify the optimal time span, but a few years are likely to match allocation policies' time frame.

The different measures we have used all point in the same direction. Herding in aid allocation is present. However its exact size depends on how we think it should be evaluated. Yearly allocations in a pure cross country framework return a limited size but may be contaminated by random variations. Longer

Table 2

Average Herding, *LSV* and *h* Measures, 3 and 5-Year Data, All Donors

3-year periods		5-year periods	
LSV	*h*	*LSV*	*h*
3.37 (1670)	11.20	4.44 (974)	12.92

Source: Authors based on OECD data. Number of observations in parentheses.

periods reveal larger herding levels that have important consequences for aid recipients. Using all the different approaches, the measure h estimates herding to be between 6 and 12 per cent.

VI. HERDING DETERMINANTS

Which factors cause donors to act similarly? By subtracting debt relief, humanitarian and food aid from official development assistance, some of them have already been excluded from our analysis. Others are expected to influence donors in a similar fashion: political transitions that promote or jeopardise democracy, armed conflicts, income shocks, etc. This section quantifies the effect of those observable shocks that create herding.

As argued in Section II, such allocation changes can be regarded positively. Following a democratic transition, donors may all respond to better governance and more transparent institutions with increased aid flows to further foster democracy. A more nuanced view would still caution against herding even in these situations. While it makes no doubt that these constitute valid reasons to increase aid, donors might still herd and overreact all together. Donors that do not participate in the aid splurge may fear being left out and missing some future investment or diplomatic opportunities. They may follow the crowd, increasing aid fragmentation in the country and inflating aid disbursements above the recipient country's absorptive capacity. The border between legitimate, well planned aid increases (or decreases) and herding is usually difficult to delimit. This section does not attempt this difficult exercise but provides a first study of herding determinants.

We also see this estimation as a valuable result in its own right. Beyond the issue of herding, this result sheds a new light on aid allocation. Researchers have always related aid quantities to recipients' characteristics (see Alesina and Dollar 2000, Alesina and Weder 2002, Berthélemy 2006, Berthélemy and Tichit 2004). The approach taken here is more basic as it considers the proportion of donors increasing aid, regardless of quantities. Donor decisions can be decomposed in two steps. First, they have to decide which recipients should receive more aid, and this is what is investigated here. Second, once where to increase and decrease aid is known, actual quantities are decided upon, and this is what the aid allocation literature has studied so far.

The dependent variable in the estimations is p_{it}. Because it is a proportion it only takes values between zero and one. OLS estimation is not well suited for this type of bounded dependent variable because predicted values cannot be ensured to lie in the unit interval. Papke and Wooldridge (1996) provide suitable estimators based on quasi-maximum likelihood methods. They propose a method using a generalised linear model with a logit link, the binomial family and robust standard errors. More specifically, they assume that:

$$E(p_{it}/\boldsymbol{x_{it}}) = G(\boldsymbol{x_{it}\beta})$$

where G(.) is the logistic function and $\boldsymbol{x_{it}}$ is a vector of explanatory variables. The herding measures suggest a slightly different approach because the variable of interest is $p_{it} - \pi_t$, and not p_{it}. To take the benchmark into account, however poses no difficulty. Instead of G being the logistic function $\frac{1}{1+\exp(-\boldsymbol{x_{it}\beta})}$, it is chosen to be $G(\boldsymbol{x_{it}\beta}) = \frac{\frac{\pi_t}{1-\pi_t}}{1+\frac{\pi_t}{1-\pi_t}\exp(-\boldsymbol{x_{it}\beta})}$. That is equivalent to changing the exposure of the dependent variable, or to have an offset $\ln\left(\frac{\pi_t}{1-\pi_t}\right)$. The method developed by Papke and Wooldridge (1996) can readily be applied using this function G.

Results following this estimation technique are complemented by more standard techniques using OLS with and without country fixed effects. These are not our preferred estimators due to the dependent variable being a proportion but we provide them as a further robustness check. Country fixed effects are added to remove any time-invariant unobserved characteristics that would affect herding (for instance Cuba may not fit our general model; a fixed effect removes its particular status).

1. Variables

The dependent variable in the estimations is based on the 3-year period herding. Independent variables are constructed from four different categories: economy, politics, conflict, and natural disasters. Economic variables include GDP growth and GDP per capita, from the World Development Indicators of the World Bank. Political variables are constructed from the Polity IV Project dataset. We exploit political transitions that result in more democratic or authoritarian regimes. A dummy variable is defined for each type of transition if it occurs in any of the three years of the period. Because of the 3-year structure of the data it is unclear that donors react during the same period. It might be the case when the transition is short and occurs at the beginning of the period, but not when the transition takes place in the last year of the period. To avoid missing such effects we create another dummy variable equal to 1 if there was a transition last period and not in the current period. We also use dummies for "new" countries, that is countries that gained independence[8], and for foreign

8. Countries that have not been present since 1960 are excluded from the data. Some countries gained independence later but aid flows had been recorded as early as 1960.

interventions. They take a value of 1 if the event occurred in any of the three years. GDP growth and GDP per capita are averages over the three years.

The number of deaths in a country caused by natural disasters is provided by the Emergency Events Database (EM-DAT). Figures for each year of the period under consideration are added to proxy for natural disaster intensity during the period. This number is then divided by the average population size in thousands during the period. The unit of measure is therefore the number of deaths due to a natural disaster by thousands of people. Aid in this article does not include emergency aid but natural disasters are still expected to affect the number of aid increases for various reasons. A natural disaster causes an influx of humanitarian aid and more long term investments that do not necessarily enter into this category. It also attracts attention to the affected country and may trigger simultaneous aid flows from many donors. Armed conflict data comes from the UCDP/PRIO Armed Conflict Dataset, as described in Gleditsch et al. (2002). The war dummy takes a value of 1 if there was a conflict in any of the three years of the period.

2. Results

The main empirical question is to estimate the effect of political, natural, and conflict shocks that cause similar allocation changes by donors. The first set of estimates uses 3-year data and is presented in Table 3. Column (1) uses the GLM estimator. Coefficients reported are marginal effects at the means to make them comparable with OLS estimates.

GDP per capita is significant but the size of the coefficient is extremely small given that income is measured in thousands of dollars. A transfer of USD 1000 per capita, arguably a very large change, reduces p_{it} by 1.1 per cent. The inclusion of GDP per capita is not directly linked to any shock but rather controls for different treatments towards rich and poor countries. Growth, on the other hand, is related to herding. The coefficient has the expected sign but is far from being significant.

The variable "new polity" is very large and significant, implying that "new" countries receive aid from 20 per cent more donors than the average recipient. Political transitions offer interesting results. Democratic transitions do not trigger simultaneous positive responses from donors neither during nor afterwards. On the other hand donors do react to authoritarian transitions and reduce their allocations during transitions: the proportion of donors increasing aid falls by 6 percent during an authoritarian transition. The asymmetry between the two types of transitions is rather unexpected. We would expect donors to punish transitions towards authoritarianism but to reward those towards democracy. It is only mildly the case.

Table 3

Herding Determinants, 3-Year Data

	(1) GLM	(2) OLS	(3) FE
Real GDP per capita	− 0.011***	− 0.011***	− 0.012
	(0.0023)	(0.0023)	(0.0085)
Real GDP growth	− 0.0019	− 0.0019	− 0.0011
	(0.0012)	(0.0012)	(0.0014)
New polity	0.20***	0.17***	0.15***
	(0.050)	(0.043)	(0.048)
Foreign intervention	0.038	0.038	− 0.11
	(0.065)	(0.068)	(0.10)
Democratic transition	0.0043	0.0045	− 0.00043
	(0.016)	(0.016)	(0.018)
Democratic transition, post year	0.011	0.011	0.0044
	(0.018)	(0.018)	(0.019)
Authoritarian transition	− 0.062***	− 0.060***	− 0.058***
	(0.018)	(0.018)	(0.019)
Authoritarian transition, post year	− 0.015	− 0.015	− 0.012
	(0.019)	(0.018)	(0.019)
Natural disaster	0.033**	0.027***	0.022*
	(0.013)	(0.0093)	(0.011)
Conflict	− 0.011	− 0.011	0.0015
	(0.0099)	(0.0097)	(0.014)
Conflict, post year	0.0050	0.0049	0.019
	(0.015)	(0.014)	(0.016)
Observations	1377	1377	1377
Adjusted R^2		0.045	0.021

Standard errors clustered at the country level in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. GLM estimation is done using a logit link and a binomial family. In column (1) the dependent variable is p_{it} and π_t is included as an offset. Estimates are marginal effects estimated at the mean pit. For dummy variables the marginal effect is for discrete change from 0 to 1. In columns (2) and (3) the dependent variable is $p_{it} - \pi_t$.

Natural disasters have a very significant effect. The number of deaths per 1000 persons due to natural disasters has a standard deviation of 0.46. A one-standard deviation from the mean increases the proportion of donors allocating more aid by 1.5 per cent. Finally, armed conflicts do not significantly affect herding. Column (2) replicates the results using OLS. Estimates are similar to those using GLM. Column (3) includes country fixed effects and confirms most results, with similar magnitudes. Once country time invariant characteristics are controlled for, GDP does not enter significantly in the regression. The significance levels of the GDP coefficient in column (1) was due to cross-section regression, and might have captured country fixed characteristics.[9] Having

9. Though we think 3-year data constitutes a better and less volatile indicator of herding, we also ran regressions with yearly data and found virtually identical results. They are available in Frot and Santiso (2009).

identified herding determinants, we now evaluate to what extent they explain the results of Sections IV and V.

VII. CORRECTED HERDING MEASURE

GLM estimation ensures that predicted values of p_{it} are within the interval [0, 1]. That allows us to compute hypothetical proportions had some events not happened and compute the "corrected herding measure" using the predicted proportions. OLS estimations usually provide predicted values smaller than 0 or larger than 1 and would make the exercise inconsistent. Consider a recipient year whose real proportion is p_{it} and is characterised by the vector $\boldsymbol{x_{it}}$. We want to find the proportion had the characteristics been $\boldsymbol{z_{it}}$ instead of $\boldsymbol{x_{it}}$. Using the definition of the function G, we obtain that:

$$p_{it}(\boldsymbol{z_{it}}) = \frac{p_{it}(\boldsymbol{x_{it}})}{\exp(-(\boldsymbol{z_{it}} - \boldsymbol{x_{it}})) + p_{it}(\boldsymbol{x_{it}})(1 - \exp(-(\boldsymbol{z_{it}} - \boldsymbol{x_{it}})\boldsymbol{\beta})} \tag{7}$$

The quantity $p_{it}(\boldsymbol{z_{it}})$ can be calculated by using the estimate value of $\boldsymbol{\beta}$ from the regressions. $p_{it}(\boldsymbol{z_{it}})$ is the estimated proportion of donors that would have increased aid to recipient i in year t had its characteristics been $\boldsymbol{z_{it}}$ instead of $\boldsymbol{x_{it}}$. The functional form adopted ensures, unlike a linear specification, that the number obtained can be interpreted as a proportion because it is between 0 and 1.

All the dummy variables are switched off to zero to see how much they account for herding. Natural disasters are also assumed away. Once the new proportions are obtained, it is only a small step to obtain the corrected herding measures. The only remaining issue concerns the benchmark to be used for these new measures. The observed benchmark is affected by recipients' characteristics. Changing these necessarily implies that the benchmark would have been different. To find the new benchmark we convert proportions in numbers of positive changes by multiplying them by the number of active donors in the recipient-year. That implicitly assumes that the number of donors would have been the same under the two sets of characteristics $\boldsymbol{x_{it}}$ and $\boldsymbol{z_{it}}$. While this is not necessarily the case, this assumption provides a natural way to find the new benchmark proportion and should not greatly affect the results. The new benchmark is then computed using these hypothetical allocation changes and herding measures are calculated as in Section III. Table 4 shows the effect of removing the herding determinants on the herding measures.

All the identified factors, taken together, reduce h from 11.20 to 10.63, or LSV from 3.37 to 3.24. It is a modest fall (5 and 3 per cent respectively) and

Table 4

Effects of Determinants on the 3-Year Herding Measure

	Original measure	Corrected measure
LSV	3.37	3.24
h	11.20	10.63

Source: Authors.

although some of these factors have been found to be significantly correlated with herding, they do not explain it well. In the absence of other easily identifiable factors a tentative conclusion is that the corrected herding levels reveal "irrational" herding due to some unobservable characteristics or strategic donor behaviour.

Two extreme views are available to interpret Table 4. The deviations from the benchmark must be interpreted as herding and shocks, both identified and unidentified, only serve as triggers, without any rationale. The other view is that these shocks cause "rational" deviations from the benchmark. They merely reflect conditions that cause similar allocation changes. Donors react similarly to natural disasters, not because they herd but because they all agree natural disasters call for increased aid flows. The reality is likely to stand between these two extreme views. The former seems too strong as shocks are highly unlikely to be mere triggers that provoke aid surges for no good reason. On the other hand the latter may be too optimistic. As Section VI has already argued, even if donors follow motivations based on hard facts (natural disasters, political transitions, etc.) it does not prevent them from herding when these events occur. Their response is likely to be based on a mixture of herding and sound motivations. Exactly which share herding represents remains a complex question to address.

VIII. CONCLUSION

This article proposes different ways to measure herding in aid allocation. We chose to use two measures initially developed in finance and adapted them to the specifics of foreign aid. Our different estimates all reject the hypothesis of no herding.

Its size however varies according to the measure used. Our preferred measure, using 3-year data and correcting for the bias inherent to the *LSV* measure, finds a herding level around 11 per cent. That implies that in a world where 50 per cent of all allocation changes are increases, the average recipient experiences 61 per cent of its donors changing their allocation in the same direction. In other words, half of the recipients see 61 per cent of their donors increase their allocations, and the other half sees 61 per cent decrease their aid allocations. The determinants of aid allocation, common to many donors, warn us against interpreting this quantity as "pure" herding.

We therefore moved on to estimate herding determinants. Shocks are expected to create swings in aid allocations and we primarily focused on these. Their influence has been shown to be relatively limited. It therefore remains that a large share of the measured herding cannot solely be explained by these shocks. We also see this estimation as a supplementary contribution of the article, as previous research on aid allocation has mainly focused on aid quantities but not on increased generosity from many donors simultaneously. The asymmetry we found between democratic and authoritarian transitions is a novel result in the literature.

Our strategy for measuring herding in aid allocation is a first step in an otherwise unexplored field. It is still unclear which measure would best suit our purpose. A structural model would clearly help but here again such models do not yet exist. The fact that all our indicators point in the same direction makes us confident that herding is present in aid allocation. Finding that herding does not seem to occur for observable reasons leads us to believe that some unobserved motives are driving the results. This is what we would expect if donors did not herd "rationally" and followed what others did in an informational cascade fashion with no clear rationale.

This article suggests there is still a lot to learn about donor allocation policies. It also shows that beneficial herding is unlikely to explain herding levels, which might be worrisome in a world of globalised flows. Aid allocation decisions are not pro or counter-cyclical with respect to many variables (growth, democratic transitions and wars). It implies that large aid variations are not necessarily due to identifiable factors. Donor coordination would help to prevent such variations in cases where they stood to be harmful, and perhaps boost them when they were useful.

This study leaves for future research the fundamental question of the motivations for donors to herd. It also leaves unanswered questions that we plan to investigate in the future. We have not investigated herding at the sector level. The analysis realised at the country level could be completed with a focus on sectors (education, infrastructure, water sanitation, etc.) in order to underline donor herding behaviour at that level and identify the shifting fashions that drive the aid industry, or, in another words, to identify both donor darling countries and donor darling sectors. We have not estimated the costs of herding. These could be evaluated in terms of higher volatility since the costs of volatility have already been estimated. They could also be related to overcrowding in countries or sectors, and so to inefficiencies due to aid fragmentation.

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SUMMARY

This paper investigates a claim repeatedly made, but never tested, that aid donors herd. To do so it originally uses methodologies developed in finance to measure herding on financial markets, and adapts them to aid allocation.

The motivation for studying herding is to improve our understanding of aid allocation beyond observable determinants. If herding is indeed present, then it is likely to shape aid patterns in a significant way by creating aid darlings, orphans, but also by exacerbating aid volatility.

Our approach starts by carefully defining aid to avoid including herding-prone aid, such as humanitarian aid and debt relief, and the sets of donors and recipients. Once this is done, herding is measured by directly applying the indexes used in finance to yearly aid data. Results show herding is indeed present, but that it is small. A second step is to introduce modifications to better match the characteristics of aid allocation. The most important in the paper is to change the time horizon. Unlike traders, aid donors commit to an aid partnership over several years, and yearly variations may contain a large part of randomness. Instead of year-to-year changes, we instead use 3 and 5-year allocations to measure herding. With this modification herding is still found to be present, but also of a larger size. It is now similar to what is traditionally found on financial markets.

The next, important step is to acknowledge that aid donors' allocation decisions almost surely follow similar determinants and changes in these determinants generate a lot of co-movements. Herding measures by definition interpret these simultaneous decisions as herding, when they merely reflect common views among donors (think about a natural disaster occurring in a country that dramatically increase aid needs). Herding determinants are carefully estimated and their contributions to herding measures are then removed to obtain an estimate free of the effects of observable variables that affect aid allocation. This procedure shows that, even after taking observable factors into account, herding is still present. It suggests other considerations drive herding behavior.