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Herding in Aid Allocation[§]

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Abstract

Although there exists a vast literature on aid efficiency (the effect of aid on GDP), and that aid allocation determinants have been estimated, little is known about the minute details of aid allocation. This article investigates empirically a claim repeatedly made in the past that aid donors herd. Building upon a methodology applied to financial markets, this article finds that aid donors herd similarly to portfolio funds on financial markets. It also estimates the causes of herding and finds that political transitions towards more autocratic regimes repel donors, but that transitions towards democracy have no effect. Finally, identified causes of herding explain little of its overall level, suggesting strategic motives play an important role.

Keywords: aid; herding; volatility; fragmentation.

JEL classification: F34, F35.

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I. Introduction

The literature in economics on foreign aid has so far mainly concerned itself with aid efficiency, attempting to answer the key question of whether aid indeed promotes growth. The motivation for this research agenda has been reinforced by the tough criticisms the aid industry has experienced over recent years. Among others, Paul Collier (2007), after a life devoted to development economics, in his recent book *The Bottom Billion*, argues that aid is unable to make a real difference to the world's poor. Others, such as the former World Bank economist William Easterly, regularly point out the deficiencies in aid allocation mechanisms. For instance, Easterly and Pfutze (2008) argue that aid is fragmented between many small donors in a given country, increasing transaction costs and revealing coordination failures.

After many papers 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. Much less has been said about the allocation of aid: while aid determinants have been estimated, donors' decision process in their choice of recipients, or 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. However, 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 paper is a first step in this direction. It is also part of a broader research agenda that studies donor allocation policies in order to understand the role of aid relative to capital flows. 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 grater overall herding? Because aid donors are somehow expected to play a different role to that of private investment, we believe it is to compare these different actors' actual behaviour.[1]

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

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,* written while at the University of Chicago, 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 paper offers different measures of herding to test for its presence and evaluate its size. Our results all reject the hypothesis of no herding, with its importance depending on the chosen measure and sample. We develop two indexes and apply them to different data sets. 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, both these measures are used in this paper with some variations from the finance literature to capture the specificity of aid allocation. In particular 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. Longer time periods are therefore used to account for inertia in aid allocation and eliminate some noise. Our preferred measure uses 3-year data and suggests that herding size is around 10 per cent. This 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 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.

Such a herding level may be difficult to interpret as many factors induce donors to change their aid allocations along similar lines, and so feed into herding measures. Herding determinants are therefore estimated to better understand what enters into our measures, and the effects of various shocks 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.

Finally, GLM estimates allow us to calculate the contribution of each determinant to the herding measure. Observable determinants in fact explain little of herding, with a very large share that cannot be solely attributed to political factors, natural disasters or wars. Though we must be careful in interpreting this result, these results suggest that other non-observable factors are at play, and in particular factors that relate directly to "pure" herding such as information cascades or signalling.

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 paper 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. 2008a; Djankov et al, 2008b; 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. 2008). 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 (for an analysis of fiscal and budget policy sensitivities on aid dependence, see Mejía and Renzio 2008). 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 paper 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,[2] 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 paper 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 and so does not have a great deal to say about interactions. It does not treat

[2] 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).

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.

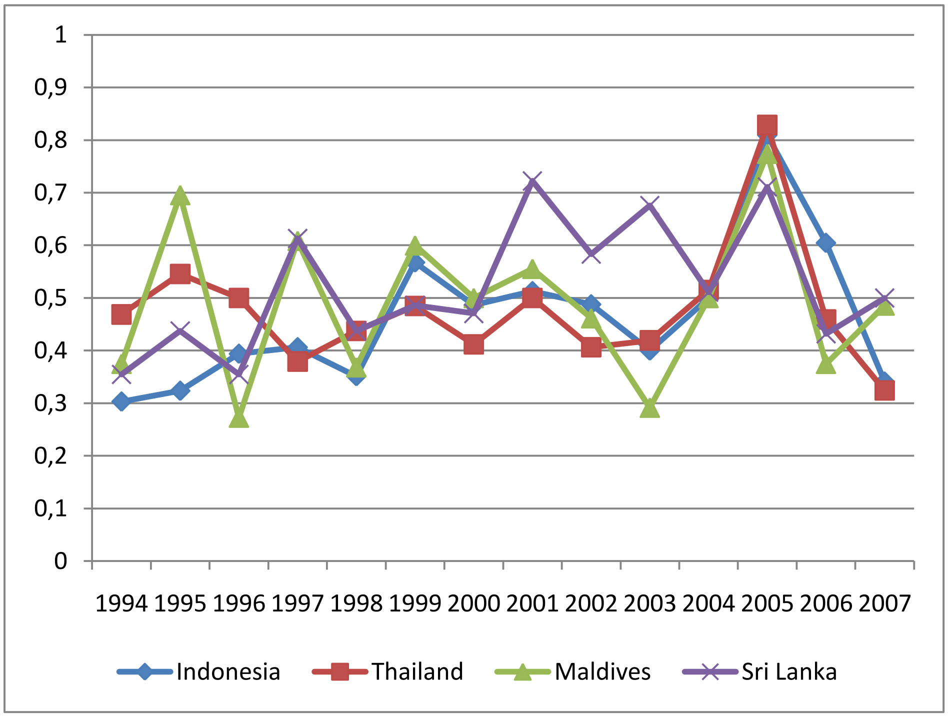
Finally, herding is potentially a force contributing to the emergence of donor darlings and aid orphans. Though her study is based on NGOs rather than on official donors, Reinhardt (2006) provides some evidence that donors do herd. She reports donor agents as saying that "we know other foundations trust 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.

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. The Asian Tsunami in December 2004 provides an excellent example of such beneficial herding.

Figure 1 plots the proportion of donors disbursing aid that actually increased their gross aid allocations compared to the year before. This proportion is calculated for four countries particularly affected by the tsunami: Indonesia, Maldives, Sri Lanka, and Thailand.

Figure 1: Proportion of donors increasing aid



Source: Authors, 2009; based on OECD data, 2009.

During the ten years preceding the tsunami the proportion of donors increasing their gross aid allocation hovers around 50 percent and remains relatively stable for each recipient, with perhaps the exception of Sri Lanka. In 2005, the year humanitarian aid was actually disbursed, the proportion jumps to about 80 percent. In this case, coordinated donor actions are beneficial. It is herding in reaction to a clear, identifiable, exogenous shock. Other examples are available: 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

a) 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

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

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, $\pi_t = \frac{\sum_i b_{it}}{\sum_i n_{it}}$ 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. Herding behaviour has been particularly pronounced in emerging markets as underlined by many studies on financial crisis spillovers (Ornelas and Alemani, 2008; Bekaert and Harvery, 2000).

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}:

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

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

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

$$h = \sqrt{H}$$

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. 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.

b) Which recipient-years? Which donors?

The OECD DAC dataset contains 5837 recipient-years where at least one donor is active.[3] 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 (Greece, New Zealand, Spain, etc.) but some also stopped after a particular year or stopped reporting their activities to the DAC. 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 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. To be on the safe side we additionally estimate herding using a constant set of donors, made of developed countries that have been disbursing aid from 1960 to 2007, the full span of the data. Any donor that enters later or stops its activity earlier is excluded. These two restrictions are quite strong because they limit the number of observations and disregard some potentially useful data.

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

[3] 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.*

and their needs created an influx of aid.[4] 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. Aid to China has been recorded only from 1979, and only from 1975 for Mongolia. Whether none was given before or whether it was not reported is unclear. These are also excluded from the set of recipient-years. Any developing country that is not in the dataset in 1960, because it did not exist at that time, or was not on the DAC list of recipients, is not taken into account when computing herding measures. This choice is also quite restrictive as it leaves aside observations where there may be herding.

An intermediate restriction is also applied. Recipients and donors entering after 1960 are included but their first five years of presence are not. It leaves some time for donors to scale aid up to new countries and reach a stabilised regime. It also allows donors to increase their allocations in their first years of presence without this affecting the herding measures.

Finally both LSV_{it} and H_{it} can be computed as soon as one donor is active in the recipient-year. Yet 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.

To sum up, donors that stop their activity are never included, those that enter after 1960 are not included, or only after their first five years. Countries whose receipts were not recorded in 1960 are excluded, or are included only after their first five years. Recipient-years with fewer than five active donors are always excluded. That leaves 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 DAC 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.

[4] It is debatable whether there was herding given their characteristics: other countries under similar conditions might not have enjoyed similar attention.

IV. Results

Table 1 presents herding measures for different groups of donors. Herding is significant in all groups, regardless of the restrictions imposed, except among multilateral donors. Those do not herd.[5] DAC donors on the other hand, do. *LSV* is always significant at the 1 per cent level. 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 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. In other words only 1 per cent of the changes in an average recipient-year cannot happen by chance and so constitute 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% 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.

[5] 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: *LSV* and *h* measures

	All donors		DAC donors		Multilateral donors	
	LSV	*h*	*LSV*	*H*	*LSV*	*h*
Donors present until 2007, recipients present since 1960	1.07 (5171)	6.27	1.05 (4866)	6.53	0.43 (3998)	4.36
Donors present 1960-2007, recipients present since 1960	1.07 (4788)	6.65	1.08 (4640)	7.08	n.a	.
5 year presence threshold	1.02 (5098)	6.03	1.11 (4865)	6.61	0.45 (3803)	4.64

Source: Authors, 2009; based on OECD data, 2009.

V. Alternative measures

The two previous measures rely on the idea of dispersion relative to an average behaviour in aid allocation. The benchmark is the same for all countries in a given year. It is a cross country reference, implicitly assuming that all countries are expected to be treated similarly in the absence of herding.

An alternative is to use past changes within countries. The expected proportion of increases in recipient i in year t would not be the proportion of increases in that year but instead the average proportion of increases in i from year $t\text{-}5$ to year $t\text{-}1$. The 5 year window is arbitrary. This measure does not assume equal treatment across countries but rather that under the assumption of no herding today's proportion of increases is expected to be close to what occurred in the last five years. The two measures are complementary as they are based on two different conceptions of herding. Like LSV_{it} it should be made neutral to changes in the global trend in aid. A proportion of increases can be far from its moving average because of herding or because the general policy in the current year is to decrease (or increase) aid. In order to shield the measure against such variations, the variable of interest is not the proportion of increases but instead the difference between this proportion and the average proportion of increases in that year. The within measure W_{it} is defined as:

$W_{it} = |p_{it} - \pi_t - \overline{p_{it} - \pi_t}| - E|p_{it} - \pi_t - \overline{p_{it} - \pi_t}|$
where the upper bar designates the 5-year moving average.

The analogue of H_{it} is $H_{it}{}^{w}$:

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

H_w and h_w are then defined in a similar fashion to H and h. An example may serve to illustrate the difference between the two measures. Assume that the proportion of increases in year t is 0.5. 80 per cent of the donors active in a given recipient i in year t increase their allocations. LSV_{it} interprets this deviation as herding. In the past five years the average proportion of increases for recipient i has been 0.75. The within measure does not see any significant difference between year t and the past and returns a non-significant herding value. The two measures do not necessarily disagree though. Had the past proportion of increases been 0.5 then both measures would return the exact same herding level.

W_{it} and $H_{it}{}^{w}$ are computed for the same group of donors and recipients as LSV_{it} and H_{it}. In order to be included a recipient-year and each of the past five years must have at least 5 active donors. If fewer than five years are available then the observation is discarded.

Table 2: *W* and *h*^{w} measures

	All donors		DAC donors		Multilateral donors	
	W	h^w	*W*	h^w	*W*	h^w
Donors present until 2007, recipients present since 1960	1.45 (4485)	6.96	1.77 (4162)	8.42	0.65 (3234)	5.21
Donors present 1960-2007, recipients present since 1960	1.90 (4113)	8.95	1.90 (3933)	9.31	n.a	
5 year presence threshold	1.57 (4656)	7.80	1.86 (4370)	8.86	0.69 (3066)	5.26

Source: Authors, 2009; based on OECD data, 2009.

Table 2 reports the results using the within measures. Herding is more pronounced when the benchmark is based on past allocations. h^w indicates values around 7-9 per cent. This means that if in the past five years on average 50 percent of all active donors increased their aid allocations then in the current year 57-59 percent take a similar decision. Values for multilateral donors are still very small.

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. It could be argued that these limited variations inflate herding measures artificially by putting some weight on random variations. These also create noise in the data that makes herding more difficult to detect.

Two solutions are proposed to address this issue. First "small" changes are not taken into account. More precisely, focusing on the most stable group of donors and recipients that includes only donors present continuously from 1960 to 2007 and recipients present since 1960, 25 per cent of all changes are smaller than USD 0.24 million (the median is 1.52, the average 11.99). If a donor changes its allocation by less than USD 0.24 million in absolute terms then it is not used to compute the two herding measures. However, the requirement that at least 5 valid donors must be active in a recipient year is not changed. Since a valid donor must change its disbursement by at least 0.24 million this condition is stronger. Second random variations are smoothed 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.

Table 3: *LSV* and *h* measures excluding small changes and with 3 and 5-year periods.

	Small changes excluded		3-year periods		5-year periods	
	LSV	*h*	*LSV*	*h*	*LSV*	*h*
Donors present until 2007, recipients present since 1960	1.32 (4573)	7.21	3.37 (1670)	11.20	4.44 (974)	12.92
Donors present 1960-2007, recipients present since 1960	1.14 (4056)	7.26	3.37 (1582)	11.98	4.25 (935)	13.61

Source: Authors, 2009; based on OECD data, 2009.

The first two columns of Table 3 indicate that the exclusion of small changes does not have a big impact on herding size. It is only slightly higher, suggesting that small variations tend to compensate each other on average. The next 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. For the same donor and recipient category, *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. If one prefers to use the *LSV* measure for both detection and size to avoid relying on any structural model, then results are even stronger with size 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 3 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. Within measures improve on the cross country ones by having the advantage of taking into account country fixed effects. Within herding is somewhat higher. Finally, year-on-year changes might not reflect decisions but be contaminated by random variations. Longer 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. Geographical distribution of herding

Even though we focus on the average level of herding across developing countries, we show here how herding differs across countries. The following map indicates herding levels in each country. Herding is computed using the *LSV* index with 3-year periods, donors present until 2007, and with more than 5 donors per recipient-period. Unlike the previous tables, we do not exclude developing countries that entered later than 1960, since the point here is to provide as comprehensive a picture as possible. Interval bounds are chosen such that each category includes the same number of countries.

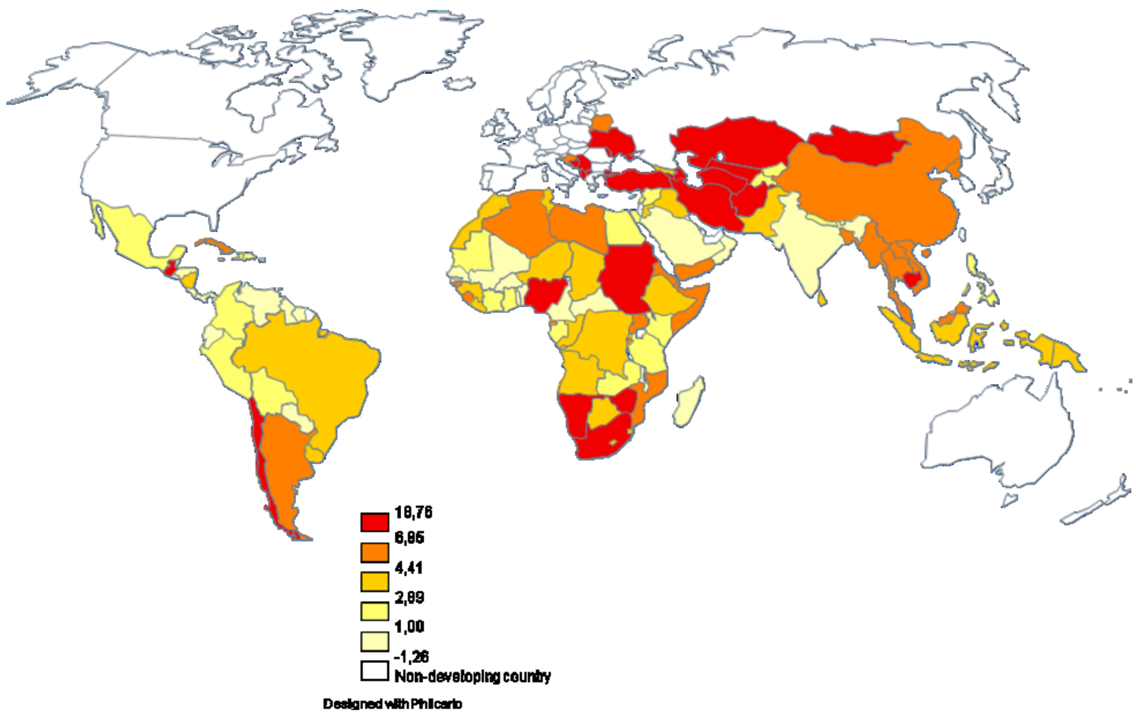


Figure 2: LSV herding, 3-year data

Source: Authors' calculations, 2009.

VII. 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. These are determinants we can take into account but must leave aside more subtle ones related to strategic behaviour or informational cascades that are more difficult to identify. 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 proper, this result sheds a new light on aid allocation to what has been done in the past. 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:

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

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}-π_t, and not p_{it}. To take the benchmark into account, however poses no difficulty. Instead of G being the logistic function $\frac{1}{1+\exp(-x_{it}\beta)}$, it is chosen to be $G(x_{it}\beta) = \frac{\frac{\pi_t}{1-\pi_t}}{1+\frac{\pi_t}{1-\pi_t}\exp(-x_{it}\beta)}$. 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).

a) Variables

The dependent variable in the estimations is based on the 3-year period herding. Yearly data maximize the sample size but are very noisy. As argued before, they are based on many small allocation changes and are unlikely to correspond to donor time horizons, but results using yearly data are still presented as a robustness check. The 3-year herding measure is calculated for two samples: one only with donors present from 1960 to 2007, the other with all the donors that do not exit the market. Both only include recipients present from 1960. The first sample offers the advantage of a stable group with no entry, but misses some large donors and may fail to capture some herding. The 3-year measure also allows for some time before a new donor actually enters the data and so measures are unlikely to be contaminated by periods of portfolio increases. To use the maximum amount of information we prefer the second measure but we also present results using the stable set of donors.

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[6] and for foreign interventions. Because 3-year periods are used, dummy variables 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 paper does not include emergency aid but natural disasters are still expected to affect the number of aid increases for various reasons. First, humanitarian aid is not reported before 1995 in the data, and so enters our aid variable before that date. Second 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.

b) 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 4. The first sample used includes all donors present until 2007. Column (1) uses the GLM estimator. Coefficients reported are marginal effects at the means to make them comparable with OLS estimates.

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[6] 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.

Table 4: Herding determinants, 3-year data

	Donors present until 2007			Donors present 1960-2007		
	(1)	(2)	(3)	(4)	(5)	(6)
	GLM	OLS	FE	GLM	OLS	FE
Real GDP per capita	-0.011***	-0.011***	-0.012	-0.0097***	-0.0095***	-0.0099
	(0.0023)	(0.0023)	(0.0085)	(0.0020)	(0.0019)	(0.010)
Real GDP growth	-0.0019	-0.0019	-0.0011	-0.0011	-0.0010	0.00012
	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0013)	(0.0014)
New polity	0.20***	0.17***	0.15***	0.21***	0.18***	0.17***
	(0.050)	(0.043)	(0.048)	(0.062)	(0.052)	(0.058)
Foreign intervention	0.038	0.038	-0.11	0.0024	0.0013	-0.22***
	(0.065)	(0.068)	(0.10)	(0.057)	(0.058)	(0.038)
Democratic transition	0.0043	0.0045	-0.00043	0.021	0.021	0.016
	(0.016)	(0.016)	(0.018)	(0.019)	(0.019)	(0.021)
Democratic transition, post year	0.011	0.011	0.0044	0.011	0.012	0.0067
	(0.018)	(0.018)	(0.019)	(0.021)	(0.021)	(0.024)
Authoritarian transition	-0.062***	-0.060***	-0.058***	-0.079***	-0.076***	-0.068***
	(0.018)	(0.018)	(0.019)	(0.020)	(0.019)	(0.020)
Authoritarian transition, post year	-0.015	-0.015	-0.012	-0.028	-0.027	-0.022
	(0.019)	(0.018)	(0.019)	(0.022)	(0.021)	(0.022)
Natural disaster	0.033**	0.027***	0.022*	0.029**	0.024**	0.018
	(0.013)	(0.0093)	(0.011)	(0.013)	(0.0099)	(0.012)
Conflict	-0.011	-0.011	0.0015	-0.0096	-0.0093	0.0073
	(0.0099)	(0.0097)	(0.014)	(0.012)	(0.012)	(0.017)
Conflict, post year	0.0050	0.0049	0.019	0.010	0.0099	0.025
	(0.015)	(0.014)	(0.016)	(0.019)	(0.018)	(0.020)
Observations	1377	1377	1377	1376	1376	1376
Adjusted R^2		0.045	0.021		0.028	0.017

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 columns (1) and (4) 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), (3), (5) and (6) the dependent variable is p_{it}-π_t.

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 not 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 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.

Contrary to what Rodríguez and Santiso (2008) found for private bank flows, there is no democratic premium in donor herding behaviour. Donors are not attracted by a democratic transition, though they shy away from authoritarian transitions. This result is consistent with previous ones underlined by Easterly and Pfutze (2008) and Knack (2004) that found no evidence that aid rewards democracy. Kalyvitis and Vlachaki (2008) found an even more disturbing result and robust evidence that aid flows are negatively associated with the likelihood of observing a democratic regime in the recipient country.

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 affect herding. Column (2) replicates the results using OLS. Estimates are surprisingly 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.

Columns (4), (5), and (6) use the same specification but restrict the sample to the fixed set of donors present from 1960 to 2007. Results are very similar. The negative impact of authoritarian transitions is even larger than with the first specification. Though we think 3-year data constitutes a better and less volatile indicator of herding, we now present results using yearly data to check whether only aggregation drives the findings. Some definitions are slightly changed to accommodate for the new frequency. The new polity dummy takes a value of 1 during the first three years of the new regime. This is to allow for a longer time span than the exact year the polity is created. Similarly, post transition dummies are equal to 1 in the two years following the last year of a transition, unless there is a transition in that specific year.

Results do not depend on the exact time frame.

Table 5: Herding determinants, yearly data

	Donors present until 2007			Donors present 1960-2007		
	(1)	(2)	(3)	(1)	(2)	(3)
	GLM	OLS	FE	GLM	OLS	FE
Real GDP per capita	-0.0051***	-0.0051***	-0.0064	-0.0051***	-0.0050***	-0.0077
	(0.00087)	(0.00087)	(0.0049)	(0.0010)	(0.0010)	(0.0057)
Real GDP growth	0.000015	0.000014	0.00026	0.00026	0.00026	0.00053
	(0.00041)	(0.00040)	(0.00041)	(0.00052)	(0.00051)	(0.00050)
New polity	0.14***	0.13***	0.13***	0.15***	0.13***	0.14***
	(0.028)	(0.024)	(0.024)	(0.028)	(0.024)	(0.024)
Foreign intervention	0.037***	0.037***	0.029*	0.052***	0.052***	-0.070***
	(0.0037)	(0.0037)	(0.016)	(0.013)	(0.014)	(0.010)
Democratic transition	0.0040	0.0040	0.0023	0.0078	0.0077	0.0047
	(0.012)	(0.012)	(0.012)	(0.015)	(0.014)	(0.015)
Democratic transition, post year	0.0055	0.0054	-0.00010	0.0047	0.0047	-0.0043
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Authoritarian transition	-0.035***	-0.034***	-0.033***	-0.038***	-0.038***	-0.039***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.014)
Authoritarian transition, post year	-0.0080	-0.0079	-0.0080	-0.027*	-0.026*	-0.027*
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Natural disaster	0.026*	0.024**	0.022*	0.020	0.019*	0.017
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Conflict	0.0089*	0.0088*	0.013*	0.014**	0.013**	0.017*
	(0.0051)	(0.0051)	(0.0077)	(0.0064)	(0.0064)	(0.0090)
Observations	3784	3784	3784	3784	3784	3784
Adjusted R^2		0.032	0.027		0.022	0.020

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 columns (1) and (4) the dependent variable is p_{it} and π_t is included as an offset. Estimates are marginal effects estimated at the mean p_{it}. For dummy variables the marginal effect is for discrete change from 0 to 1. In columns (2), (3), (5) and (6) the dependent variable is p_{it}-π_t.
Source: Authors, 2009.

Table 5 essentially confirms the results from Table 4. Yearly data exhibit the same pattern, except for a less precisely estimated effect of natural disasters. Both tables show consistent results and make us confident that they are quite robust.

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

VIII. 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 :

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

The quantity $p_{it}(\boldsymbol{z_{it}})$ can be calculated by using the estimate value of beta from the regressions. $p_{it}(\boldsymbol{z_{it}})$ is the 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 to be successively switched off to zero to see how much they account for herding. Natural disasters will also be 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 number 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.

The sample and estimates using the 3-year period data with donors present until 2007 is used. Table 6 shows the effect of each variable on the herding measure.

Table 6: Effects of each determinant on the 3-year herding measure

	Original measure	New polity	Foreign intervention	Democratic transition	Authoritarian transition	Natural disasters	Conflicts
LSV	3.37	3.35	3.35	3.35	3.30	3.26	3.24
h	11.20	10.85	10.87	10.87	10.75	10.66	10.63

Source: Authors, 2009.

Starting from the original herding measure found in Table 3, each column removes the effect of a variable. For instance, deducting herding caused by new polities reduces *h* from 9.83 to 9.76. Foreign intervention and democratic transition hardly change this result. Authoritarian transition and natural disasters have a larger effect. Conflicts also reduce herding but this should be taken with caution given that the regressions in Table 4 did not show any significant effect of conflicts. All the identified factors 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 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 6. The deviations from the benchmark must be interpreted as herding and these events only serve as triggers, without any rationale. The other view is that these events 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.

IX. Conclusion

This paper 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, instead of similar responses to similar factors.

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 paper, 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 paper 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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