Do the Bretton Woods Institutions Promote Economic Transparency?*

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Abstract

Disseminating data is a core mission of international organizations. The Bretton Woods Institutions (BWIs), in particular, have become a main data source for research and policy-making. Due to their extensive lending activities, the BWIs often find themselves in a position to assist and pressure governments to increase the amount of economic data that they provide. In this study, we explore the association between loans from the BWIs and an index of economic transparency derived from the data-reporting practices of governments to the World Bank. Using a matching method for causal inference with panel data complemented by a multilevel regression analysis, we examine, separately, loan commitments and disbursements from the IMF and the World Bank. The multilevel regression analysis finds a significant association between BWI loans and the improvement of economic transparency in all developing countries; the matching method identifies a causal effect in democracies.

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1 Introduction

Disseminating economic data is a central mission of both the World Bank (WB) and the International Monetary Fund (IMF). The *World Development Report*, produced annually by the WB, has been the definitive repository for country-level aggregates since the 1970s, and the institution explicitly re-branded itself as a "Knowledge Bank" in the 1990s (Kramarz and Momani, 2013). The IMF describes itself "as a global hub for knowledge on economic and financial issues,"[1] and its *International Financial Statistics* is the authoritative source for financial and macroeconomic data for 194 countries.

These financial institutions—together known as the Bretton Woods Institutions (BWIs)—also provide loans and grants to member states for development and stabilization purposes. This study suggests that the BWIs enhance the economic transparency of recipient countries through their lending activities. Governments that borrow from the BWIs provide more credible economic data of sufficient quality to be published in the WB's *World Development Indicators*.

BWI loans can encourage the disclosure of data through two mechanisms. First, BWI loans enhance a state's capacity for providing data, by freeing resources for improvements in a state's data infrastructure. BWI lending arrangements also typically offer technical expertise in data collection, aggregation, and dissemination. Second, BWI loans enhance a state's willingness to provide data—the policy conditions associated with the loans often include requirements to report key financial and economic data back to the lender.

Existing theory contends that transparency can destabilize autocracies, while transparency strengthens democratic regimes (Hollyer, Rosendorff, and Vreeland, 2015, 2019). Autocracies may therefore be disinclined to increase transparency of their own volition. If BWI lending increases transparency in autocracies, it is likely due to coercion—e.g. loan conditionality. By contrast, if democracies are only limited in providing economic data by state capacity, then BWI loans might help to increase economic transparency through the resources that they provide governments. Of course, there are domestic and international strategic considerations that may discourage gov-

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[1]See `https://www.imf.org/en/Capacity-Development/how-we-work`, accessed July 29, 2020.

ernments from disclosing data—lest opponents at either level learn that the government is a better, or worse, performer than generally assumed. So it is not *a priori* clear that either regime would succumb to BWI encouragement or pressure to improve data reporting practices.

This paper offers rigorous empirical tests of the relationship between BWI loans and economic transparency. The HRV index (Hollyer, Rosendorff, and Vreeland, 2014), which treats economic transparency as a latent predictor of the reporting of data on 240 economic variables to the WB for publication in the *World Development Indicators*, is our dependent variable. The predictor is estimated using a Bayesian item response model, based on an underlying dataset covering 125 countries for the 1980-2010 period.

The HRV index is derived from the full spectrum of economic indicators that national governments report to international organizations. The largest movements in the index are driven by indicators with high "discrimination" scores: the current account balance, goods and services exports, and changes in foreign reserves. These also happen to be critical for BWI lending. Other items with high discrimination scores (leading to more variable rates of reporting) include private capital flows, foreign direct investment figures, and additional trade related data.[2]

This index measures the presence or absence data, not the quality of the data *per se*. The *World Development Indicators* has explicit standards for data quality, so the index captures at least some minimal level of data quality. Governments may have strategic reasons to manipulate data however, and low quality data are sometimes accepted and misreported by international organizations (see, e.g., Kerner, Jerven, and Beatty, 2017). HRV primarily reflects data reporting, and only crudely captures data quality—a more fine-grained measure would be necessary to capture more subtle forms of manipulation.

As explanatory variables, we consider loan commitments and, separately, their disbursements to governments from the two BWIs. Given existing work on transparency and regime type, we test for regime-specific effects of BWI commitments and disbursements, in addition to testing for pooled effects on all countries.

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[2]See Hollyer, Rosendorff, and Vreeland (2018, 54-56).

Empirically, there are two major sources of confounding that we address in the analysis: possible selection bias and carry-over effects. Because these organizations are devoted to promoting data disclosure, transparency itself may be an important factor that influences who receives BWI loans. For example, loans may be more likely to be assigned to governments that have high potential to improve their economic transparency. Relatedly, carry-over effects are common concerns in panel data analysis with a reversible treatment. Recent previous participation in BWI programs may systematically change the incentive of a government to work with BWIs in a later program, which would violate the stable unit treatment value assumption (SUTVA) and lead to biased estimates of the effect of loans on transparency.

To identify the effects of BWI loans on transparency, we take advantage of recent developments in causal inference with panel data (Imai, Kim, and Wang, 2021). *PanelMatch* adjusts for carry-over effects by matching observations with an identical treatment history for a pre-specified time span. It corrects for selection bias by refining the matched sets by weighting or matching on covariates, and applies a difference-in-differences estimator to correct for a possible time trend and to estimate short- and long-term effects.

This matching approach to causal inference is not without limitations. The analysis achieves high internal validity—on the treated observations that have matches—at the expense of external validity, discarding the many observations that do not match. This turns out to be particularly serious for the WB data, which has a relatively small set of matched observations. Also, the method requires the treatment to be discrete and cannot investigate the effect of loan size as a continuous treatment.

We complement the *PanelMatch* approach with multilevel regression models, estimating the heterogeneous associations between loans and transparency across political regimes by fitting varying coefficients models. We include country-, year-, and regime-specific intercepts to control for unobserved confounding in multiple dimensions that cannot be matched on when using the *Panel-Match* approach.

We find that loan disbursements and commitments from the IMF and the WB are positively as-

sociated with economic transparency, and these associations are likely to be causal in democracies.

The scholarly community has become increasingly aware of the ways in which missing data plagues empirical research. Missing data also stands as an obstacle to policymaking as well as the work of nongovernmental organizations and activists. While the bulk of research on the BWIs focuses on the economic and political effects of their lending activities, disseminating data remains a core mission of these institutions. Our findings show that their lending activities, which are often critiqued for falling short of achieving economic goals, succeed in furthering the objective of promoting greater data availability—at least for democracies. As has been found in many other areas of research on BWIs, objectives are more readily achieved with they align with the political will of recipient governments. We conclude that BWI loans help democracies generate the public good of economic information.

These results are first steps towards understanding the broader relationship between international organizations and transparency. Further questions include whether BWI loans enhance other facets of transparency, including freedom of the press, the presence of freedom of information laws, and the disclosure of human rights practices. There are also broader questions to be addressed about the effects of other types of international organizations. Does development assistance from regional development banks enhance economic transparency? How does their effectiveness compare with that of China's new Asian Infrastructure Investment Bank (AIIB)? What are the effects of bilateral aid, and do they differ across democratic and autocratic creditor countries? This paper offers a state-of-the-art empirical framework to pursue the effects of alternative international institutions, assistance and other interventions on economic and other facets of transparency.

2   IOs and Data Collection and Dissemination

2.1   The Bretton Woods Institutions

The WB started publishing the *World Development Report* in the 1970s, and it made knowledge-sharing one of its central purposes in the early 1980s. The WB has more publications and a higher

citation rate per publication than the IMF, the OECD, the Brookings Institute, and the International Institute of Economics—with the IMF in second place (Kramarz and Momani, 2013, 422).

The IMF similarly identifies information sharing as a central purpose. In the 1990s, the IMF, working in collaboration with the WB, established the General Data Dissemination System (GDDS), the Special Data Dissemination Standard (SDDS), and the Data Quality Assessment Framework (DQAF).[3] All members of these organizations have access to technical assistance through the GDDS or the SDDS.

While participation in these frameworks and standards is largely voluntary, BWI programs can require the collection of data relevant to the performance and creditworthiness of borrowing states. The IMF has leverage explicitly built into their loans through conditionality, whereby recipient governments are required to adopt specific policies in return for continued disbursements of the loans. Conditionality famously targets macroeconomic policies, but policy conditions can also explicitly include data requirements.[4] The IMF staff requires national statistics in order to monitor compliance, and to refine its policy advice based on local conditions. Loan-conditioned scrutiny of economic aggregates has led the IMF to collect previously missing or update erroneous economic data. In 2000, for example, the government of Pakistan admitted that the previous administration fudged tax data reported to the IMF; in a 2001 IMF arrangement, the government committed to "progress in tax administration reforms, and progress in monitoring fiscal expenditure" (Vreeland, 2002). As part of their 2010 arrangement with Greece, the IMF required the "strengthening of public sector reporting mechanisms, including statistical aspects" after the country was condemned for falsifying data in the run up to the country's sovereign debt crisis in 2009 (Wyplosz and Sgherri, 2016, 33). While the IMF staff provides helpful guidance on data collection best practices, assisting governments with their capacity to collect data, policy conditionality gives the organization

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[3]For background, see `https://dsbb.imf.org/e-gdds/overview`, `https://datatopics.worldbank.org/debt/gdds-methodology`, and `http://data.worldbank.org/about/data-overview/data-quality-and-effectiveness`, accessed August 11, 2020. Also see Mosley (2003) and Cooray and Vadlamannati (2015).

[4]See, for example, Dreher, Sturm, and Vreeland (2015, 123-124), `https://www.imf.org/en/About/Factsheets/Sheets/2016/08/02/21/28/IMF-Conditionality`, and `https://www.imf.org/external/np/pdr/mona/ArchQPC_Codes.htm`.

leverage to overcome a government's potential lack of willingness to share data publicly.

The WB does not rely as much on policy conditionality *per se*, but development project loans require the WB staff to approve only projects that are suitable for local conditions. Ultimate project approval is subject to an executive board decision, and the loan commitment stage can be held up indefinitely without proper economic justification—which requires data. Thus the WB enjoys leverage over governments at the commitment stage (although, lacking policy conditionality for many of their loans, they do not necessarily enjoy the same leverage as the IMF during the disbursement phase). So, similar to the IMF, the WB can have a good relationship with a government, providing friendly advice on best practices, but the WB can also play a coercive role, particularly at the commitment stage.

The BWIs require effective data collection and reporting in order to design, implement, and monitor the programs and projects that their loans are designed to support. The evidence of their effectiveness however, is mixed. Cooray and Vadlamannati (2015) do not find any effect of participation in an IMF program on transparency. By contrast, Hollyer, Rosendorff, and Vreeland (2011) find a positive and statistically significant effect for a dichotomous indicator for IMF participation. These studies treat these indicators as control variables and neither focuses on empirical issues such as selection bias or carry-over effects. Neither study examines IMF loan commitments or disbursements (only program participation), nor do they consider the effects of WB lending.

2.2   Recipient States

All governments have a predisposition towards opacity. The glare of the media or the public eye may inhibit the implementation of preferred policies, or limit opportunities for rent seeking, patronage, and extortion. Too much information about government under-performance can activate political opponents in legislatures, or offer a focal point around which protest and mass political action can coordinate (Bueno de Mesquita and Downs, 2005). Data on (poor) economic performance may be beneficial to one's political opponents, and a public "bad" to government or regime supporters.

Data transparency has implications for a government's international relations too. If rival states recognize that a country is a better (or worse) performer than generally assumed, disclosure can generate strategic weaknesses. Indeed, it is not obvious that augmenting the informational environment is always optimal for international negotiations (Carnegie and Carson, 2018, 2019, 2020). Data disclosure is not without controversy.

Transparency is also costly. Obtaining information about the economy may require effort—a free and inquiring media, the availability of freedom of information requests, an open system for collecting, aggregating and sharing data and knowledge: all require resources to establish.

Data transparency also has economic and political benefits. Better data improves resource allocation, reducing inefficiencies from imperfect information. Investment (both domestic and foreign fixed) increases with transparency (Hollyer, Rosendorff, and Vreeland, 2018, ch. 8), which improves economic performance and wages, especially in labor abundant states. Transparency also reduces the volatility of economic aggregates, all potentially enhancing the political survival of leaders (Mansfield and Reinhardt, 2008; Hollyer and Rosendorff, 2012; Shambaugh and Shen, 2018). Sometimes leaders use transparency to divert responsibility for poor economic outcomes—blaming external events rather than poor policy choices—and providing the data to prove it (Rosendorff, 2005).

Leaders balance the political and economic costs and benefits of transparency differently, resulting in varying levels of observed transparency. What might affect this balance, and shift the level of economic transparency a state provides? Firstly, improvements in the ability to collect, aggregate and disseminate information reduces the costs of transparency. Economic transparency has been found to rise with GDP per capita, suggesting that capacity constrains information flows (Hollyer, Rosendorff, and Vreeland, 2018, ch. 4). BWI loans might be able to help address capacity constraints. To the degree that a loan is conditioned on, and used for, improvements in capacity, it can lower the costs of data collection, and shift the balance towards providing more information about economic policies and outcomes.

The prospect of a BWI loan might also impact a leader's willingness to provide information. A

leader may be willing to tolerate more transparency—risking coordination of political opponents, or exposure of corruption or maladministration—in return for BWI loans. The loans might be used to buy political support, reward cronies, fix investment and infrastructure, or pay down debt. When a loan is conditioned on enhanced transparency, a reluctant leader may concede to improved transparency in order to access "free" resources useful for enhancing survival in office.

Leaders are constrained by both state capacity and their own willingness to supply economic data to the public. BWI loans reduce the economic costs of informational collection and aggregation, and may enhance political prospects for leaders if the extra resources offset any potential risk of coordination by political rivals. We expect BWI loans to cause an increase in transparency.

2.3 Regime Type

Many scholars contend that democracy is practically synonymous with transparency (Broz, 2002). While democratic institutions may pressure governments to focus their efforts on highly visible policy areas over the obscure (Mani and Mukand, 2007) and they may actively seek to obfuscate certain policy areas (Kono, 2006; Berliner and Erlich, 2015), they still tend to disclose data at higher rates than autocracies.[5] In general, transparency helps stabilize democratic regimes, attract investment, and improve governance and reelection chances for leaders (Hollyer, Rosendorff, and Vreeland, 2018). Democracies, therefore, are generally more willing to be transparent—-even when controlling for capacity.

Autocracies, by contrast, often resist sharing information publicly. Opacity makes it easier to reward political insiders for their support with draws from the national fiscus. Opacity permits leaders with fewer institutional constraints to engage in corruption or rent extraction, with little concern for angering rival elites or the polity at large (Boix and Svolik, 2013).

Autocrats can more easily manage the threat of unrest among the masses when individuals are ignorant of what other citizens think of their government's performance. Routinely withholding

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[5]See Besley and Burgess (2002); McMillan and Zoido (2004); Berliner (2014); Kosack and Fung (2014); Copelovitch, Gandrud, and Hallerberg (2018).

credible information about the economy may not stave off an individual's distaste for her government, but it does leave her in the dark as to what others think. When economic data is shared, it informs the higher-order beliefs of citizens, making it easier to coordinate on public displays of discontent with the ruling regime. Mass unrest becomes more likely with increased economic transparency (Hollyer, Rosendorff, and Vreeland, 2015).

We should therefore anticipate substantial differences in the tendency to disclose *ex ante*, before any BWI loan commitments or disbursements, across regime-types (Bueno de Mesquita et al., 2003; Hollyer, Rosendorff, and Vreeland, 2011). These differences may also impact the mechanisms linking BWI lending to governments' tendency to disclose. For instance, the logic posited in the literature—that democracies have a stronger inherent incentive to disclose information than autocracies—implies that loan conditionality is more relevant for the latter than for the former. Autocrats will only disclose more information when coerced into doing so; democratic leaders may wish to increase disclosure even absent external pressures. This might argue for a larger effect of BWI lending—and particularly IMF lending, given its heavy use of conditionality—on transparency under autocratic rule. Conditionality induces autocrats to disclose where they otherwise would not. Democrats, by contrast, were already in compliance with such conditions, and so conditionality does little to alter their behavior (Downs, Rocke, and Barsoom, 1996).

In contrast, democracies might be impacted more by the financial resources and expertise that come with BWI programs. Democratic governments have a stronger incentive to make use of BWI resources to improve their states' statistical practices. Autocrats, on the other hand, face little incentive to increase transparency beyond the bare minimum required as part of the conditions attached by the BWIs to their loans. This mechanism—one mediated by the effect of lending on state statistical capacity—might lead one to anticipate that BWI lending would have a larger effect on transparency under democratic rule.

No doubt other mechanisms may also give rise to discrepancies in the effect of BWI lending across regime-types. In our statistical analyses below, we fit models that allow for such heterogeneity. Our theoretical discussion does not provide a clear expectation for the direction of these

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effects; it does provide a strong basis to believe that such heterogeneity might arise. We treat any such discrepancies as offering suggestive evidence regarding which causal effects are most likely to link BWI lending to transparency scores: if loan conditionality and coercion dominate, the effect on transparency will be greater in autocracies; if capacity improvements dominate, the democratic states will be more responsive to BWI lending than their autocratic contemporaries.

3 Data

3.1 Measuring transparency

The HRV Transparency Index treats economic transparency as a latent predictor of member-states' reporting of data on 240 economic variables to the WB for publication in the *World Development Indicators (WDI)*. The variables include only measures that national governments collect; surveys and indicators constructed by other parties are excluded. The WB makes its data broadly available, and governments are unlikely to be able to hide this information from other audiences.

The index is estimated using a Bayesian item response model where $z_{j,c,t} \in \{0,1\}$ denotes an indicator equal to 1 if country c reports *WDI* variable j in year t and equal to 0 otherwise:

$$Pr(z_{j,c,t} = 1 | transparency_{c,t}) = logit(\delta_j + \beta_j transparency_{c,t}) \tag{1}$$

where δ_j is a parameter estimating how difficult the data on variable j are to collect (compared to other variables in the estimation) and β_j is a discrimination parameter estimating how well patterns of missingness for item j predict patterns of missness for other variables in the estimation. The term $transparency_{c,t}$ is the estimated index of a given country-year's propensity to disclose data.

The main dataset is available for 125 countries for the 1980-2010 period, for a maximum of 3,875 observations. In our effective sample, the dependent variable, $transparency_{c,t}$, ranges from -10.870 to 9.981 with mean 1.178 and median 0.773; the distribution is right-skewed. As Figure 1(a) shows, the majority (61.755%) observations are greater than zero and more than 1000

negative observations are concentrated in the interval of $(-1, 0)$. Figure 1(b) separates the observations by regime and plots stratified distributions. It shows that democracies (mean 2.54, sd 2.22) average higher transparency than autocracies (mean -0.52, sd 1.65), suggesting concerns about heterogeneity across regime-type. Our measure of regime type is the binary {0,1} drawn from Cheibub, Gandhi, and Vreeland (2010).
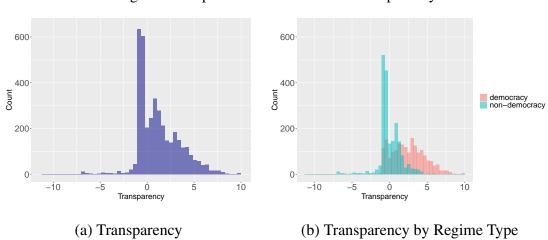
Figure 1: Empirical Distributions of Transparency

(a) Transparency

(b) Transparency by Regime Type

3.2 BWI loan commitments and disbursements

To measure the effect of BWI arrangements on economic transparency, we consider loan commitments and, separately, their disbursements to governments. We consider gross—not net—disbursements, and we test for pooled effects on all countries as well as regime-specific effects.

In our sample, governments receive, on average, about 165.26 and 184.77 million US dollars (USD) in loan commitments and disbursements annually, respectively, from the WB.[6] Governments receive, on average, 116.1 and 34.07 million Special Drawing Rights (SDR) as commitments and disbursements, respectively, from the IMF (about 166.65 and 48.90 million USD at current market rates) between 1980 and 2010.[7] The average amounts of IMF and WB loan com-

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[6]World Bank Finances' IBRD Statement of Loans - Historical Data, `https://finances.worldbank.org/Loans-and-Credits/IBRD-Statement-Of-Loans-Historical-Data/zucq-nrc3` (accessed October 21, 2020).

[7]IMF Finances' Financial Data Query Tool, `https://www.imf.org/external/np/fin/tad/query.aspx` (accessed August 12, 2020).

mitments are similar, but sample-average IMF loan disbursements are much smaller than sample-average IMF loan commitments and also much smaller than sample-average WB disbursements. IMF loans are concentrated on a smaller set of country-years than the WB loans: Among the sample country-years, the proportion receiving loan commitments and disbursements from the WB is 0.537 and 0.588 respectively, compared to 0.141 and 0.098 from IMF. Among the 125 countries in the sample, 93 receive IMF loan commitments at some point, 84 receive IMF loan disbursements; for WB loans, 99 countries receive both loan commitments and disbursements.
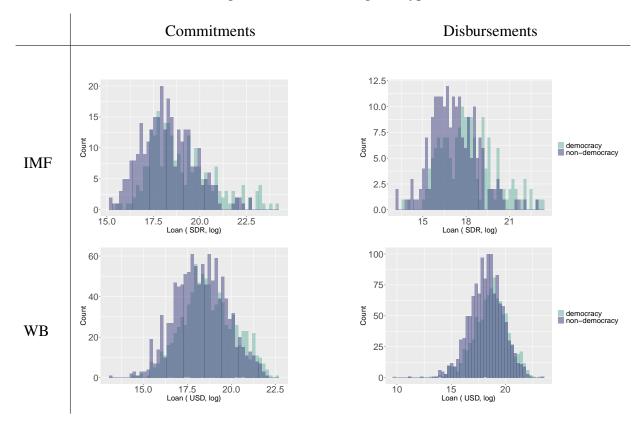
Among those country-years under "treatment," the average amount of loan commitments is 307.57 million USD and 821.28 million SDR (1,178.52 million USD) from the WB and the IMF respectively, and that of loan disbursements is 314.44 million USD and 348.38 million SDR (499.89 million USD). Figure 2 reports the distributions of how many years a country receives loan commitments or disbursements from the BWIs. Figure 3 shows the distributions of loan commitments and disbursements from the IMF and WB to democracies and autocracies.

Figure 2: Distributions of Loans across Time

| IMF Commitments | IMF Disbursements | WB Commitments | WB Disbursements |

Note: WB loans occur more frequently and last longer. The scales of the y-axis are different across the IMF/WB panels.

Figure 3: Loans and Regime Type

Note: Histograms of loan commitments and disbursements by the IMF and WB, stratified by regime type. The distributions are similar across the BWIs. Figures S1 and S2 report the full treatment assignment plots.

3.3   Control variables

If confounders simultaneously affect the decision-making of loan commitments or disbursements and the level of transparency, we may have selection bias. Also, because the BWI's are committed to promoting economic transparency, the potential to improve transparency may be an important factor that they consider, suggesting an endogeneity problem. Analysis of our data reveals associations that justify these concerns. Table 1 shows the association between loan commitments/disbursements and the level of transparency, by regressing each of them (separately) on the HRV index. The BWIs appear to be more likely to provide loans to *less* transparent countries—especially less transparent democracies. Among autocracies, however, the evidence suggests that

Table 1: Possible Selection Problem: How BWI Loan Assignment is "affected" by transparency

Model	Loan	IMF Loan Commitment	IMF Loan Disbursement	WB Loan Commitment	WB Loan Disbursement
Pooled	Size	−0.149***	−0.141***	−0.393***	−0.501***
		(0.046)	(0.038)	(0.065)	(0.064)
	Dummy	−0.050***	−0.061***	−0.066***	−0.081***
		(0.011)	(0.013)	(0.009)	(0.009)
Democracy	Size	−0.373***	−0.349***	−1.372***	−1.286***
		(0.067)	(0.055)	(0.095)	(0.095)
	Dummy	−0.118***	−0.148***	−0.212***	−0.194***
		(0.019)	(0.022)	(0.015)	(0.015)
Autocracy	Size	0.229**	0.159*	1.471***	1.157***
		(0.090)	(0.075)	(0.121)	(0.118)
	Dummy	0.048*	0.043	0.210***	0.155***
		(0.022)	(0.024)	(0.021)	(0.019)

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Estimated coefficients of transparency on BWI loan commitments or disbursements. Less transparency is associated with a higher probability of receiving a loan (Dummy/Probit) as well as receiving larger loans (Size/Linear). The relationship appears in the democracy subsample, but not among autocracies.

BWIs are more likely to provide loans to the goverments that provide more publicly available data. These patterns hold for both BWIs, although more so for the WB.

To correct for potential selection bias, we control for variables that are likely to explain BWI loan distributions and are also associated with economic transparency. Those variables include the level of transparency in the previous year, GDP per capita, population and GDP, trade as percentage of GDP, the number of signed bilateral investment treaties, and whether a country is a WTO member. Political instability is also likely to be associated with both BWI loan decisions and transparency.[8] Developing countries are more likely to receive BWI loans during high-profile years in the international arena, so we control for an indicator of membership on the United Nations Security Council (UNSC). Region could be another predictor of economic transparency, and, at the same time, it is likely that the distribution of BWI loans is systematically different across

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[8]The data are from Major Episodes of Political Violence 1946-2019, https://www.systemicpeace.org/warlist/warlist.htm.

regions. We further control for the geographical distance between the capital of a country and the headquarters of IMF and WB.[9] Finally, we correct for time-trends in the matching/causal inference analysis and unobserved heterogeneity across countries and regimes and over time in the regression analysis.

All control variables are lagged by one time period. A small portion of the data is missing, and these missing values are imputed, resulting in an effective sample size of 3,750 country-year observations.

4   Methods: Panel matching and multilevel regressions

When dealing with panel data with reversible treatment, another source of endogeneity emerges from possible carry-over effects. A country that recently received a loan might be more (or less) likely to receive another. Treatment history matters, and the effect on transparency is not only determined by the current treatment status but may be also affected by the treatment assignment in previous years. Such carry-over effects violate the aforementioned SUTVA, and biases the estimated effects of interest.

4.1   A matching method for panel data

To address the problems of selection and carry-over effects, we apply the *PanelMatch* method (Imai, Kim, and Wang, 2021), which uses an extended difference-in-differences (DiD) design. *PanelMatch* adjusts for possible carry-over effects by matching observations with an identical treatment history for a pre-specified time span. Then it corrects for selection bias by refining the matched sets with covariate-weighting. Finally, it applies a DiD estimator to adjust for a possible time trend and to estimate short- and long-term effects.

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[9]Data are downloaded from https://gist.github.com/ofou/df09a6834a8421b4f376c875194915c9, double-checked with https://www.kaggle.com/datasets/juanmah/world-cities.

This method estimates the following causal estimand:

$$\delta(F, L) = \mathbb{E}[Y_{i,t+F}(X_{it} = 1, \ X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L}) -$$

$$(Y_{i,t+F}(X_{it} = 0, \ X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^{L}) | X_{it} = 1, \ X_{i,t-1} = 0] \qquad (2)$$

where δ is the average treatment effect of the treated (ATT), and $\delta(F, L)$ indicates the ATT at the Fth period after country i is financed at t, by adjusting for carry-over effects back to L periods before the treatment. X_{it} is the binary treatment variable, and it is defined as whether country i is financed by a BWI at time t. The first term on the right-hand side in Equation (2) is the observed treated outcome, and the second term is the counterfactual. Here, country i needs to experience a change of treatment state from $X_{i,t-1} = 0$ to $X_{i,t} = 1$.[10] The counterfactual outcome is defined as experiencing no such a change: $X_{i,t-1} = 0$ to $X_{i,t} = 0$. The term, $\{X_{i,t-l}\}_{l=2}^{L}$, is the treatment history back L periods.

The method corrects for the carryover effect for L periods by defining the counterfactual not only considering the treatment status at $t-1$ and t, but requires the identical treatment history back to L periods of the factual and counterfactual. We choose a value of L to improve the credibility of the limited carryover effect assumption (Imai, Kim, and Wang, 2021, 7). But F is suggested to be chosen based mainly on substantive interest.

To estimate the causal effect, *PanelMatch* uses the following DiD estimator:

$$\hat{\delta}(F, L) = \frac{1}{\sum_{i=1}^{N} \sum_{t=L+1}^{T-F} D_{it}} \sum_{i=1}^{N} \sum_{t=L+1}^{T-F} D_{it} \left((Y_{i,t+F} - Y_{i,t-1}) - \sum_{i' \in \mathcal{M}_{it}} w_{it}^{i'} (Y_{i',t+F} - Y_{i',t-1}) \right)$$

$$(3)$$

This estimator takes three steps: (1) for each treated observation indexed by it, we construct a matched set $\mathcal{M}_{it}$ of control units that share the identical treatment history from time $t - L$ to $t - 1$;

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[10]When the quantity of interest is the average treatment effect on the control group, then the change of treatment state should be from $X_{i,t-1} = 1$ to $X_{i,t} = 0$ at t. Therefore, to estimate the average treatment effect (ATE) requires two matched sets, one with the treatment status from 0 to 1, and the other, the reverse. Our sample data cannot support the estimation of ATEs in regime-specific analysis. Therefore, we focus on the estimand of ATT.

(2) then we use a set of covariates $\mathbf{Z}$ to construct the weights $w_{it}^{i'}$ for each of matched control units i' in $\mathcal{M}_{it}$ to correct for selection bias; and (3) we apply the DiD estimator in equation (3) to adjust for a time trend from $t - 1$ to $t + F$ and estimate ATT for $F = 0, 1, 2, ...$, i.e., the instantaneous, short-run and long-run (cumulative) effects. The standard error of ATT is computed using a block bootstrap procedure. We utilize the R package *PanelMatch* 2.0 for the analysis. To calculate regime-specific ATTs, we specify the "moderator" argument as the democracy indicator.[11]

This approach faces limitations. The analysis achieves high internal validity at the expense of external validity—features of our data lead *PanelMatch* to discard many treated observations. For the IMF analysis, the ratio of the number of matched treated observations to the total number of the treated observations is between 35% to 76% in the stratified and pooled analysis; for the WB the ratio is below 10%. Another shortcoming of the matching method is that it requires treatment to be discrete and cannot be used to investigate the effect of changes in the size of the loan. The average dose of IMF loans is very different from that of the WB (see Figure 3), and the size of loans size may be important in the degree of pressure the BWIs can apply. Moreover, the matching method is unable to correct for bias caused by unobserved attributes of countries.

4.2 Multilevel analysis

To investigate the external validity and generalizability of our results, we complement the causal inference with multilevel analysis. This approach also allows us to employ (approximately) continuous terms—i.e., the size of loan commitments and distributions—as explanatory variables. We use multilevel modeling to estimate the heterogeneous effects of BWI loans on transparency across political regimes by specifying varying-coefficient models, including the same controls as in the *PanelMatch* method. With multilevel modeling, we can control for unobserved heterogeneity with country-, year-, and regime-specific intercepts effects. The multilevel analysis stratifies by regime (as in the causal inference analysis), but uses all the information and treats the sub-samples as co-

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[11]The "moderator" argument allows the estimation of ATT based on matched sets that do not precisely match on regime type. In contrast, split-sample matching necessitates that counterfactuals are drawn from countries of the same type.

existing in a larger population. We consider both the intensive and extensive margins of loans—not just the presence of a loan but also its size. Information-based criteria, such as AIC, BIC, and log likelihood, can be used to decide whether the effects of BWI loans vary across regimes.

In addition, the effects estimated in *PanelMatch* only apply to the "treated" due to the limitation of our sample. In other words, we only know whether receiving loans affects transparency on the countries that actually receive the loans. But the relationship between loans and transparency estimated in the multilevel modeling is the average over both the "treated" and the "control" observations.

We use the following specification to conduct multilevel analysis:

$$y_{it} = \alpha_0 + \alpha_i + \alpha_t + \alpha_{j[it]} + \rho y_{i,t-1} + \beta_{j[it]} loan.IO_{it} + \boldsymbol{\beta}_1 \mathbf{Z}_{it} + \epsilon_{it} \tag{4}$$

$$\alpha_j \sim \mathcal{N}(0, \sigma_{1j}^2), \ \beta_j = \beta + \epsilon_j, \ \epsilon_j \sim \mathcal{N}(0, \sigma_{2j}^2) \tag{5}$$

$$\alpha_i \sim \mathcal{N}(0, \sigma_i^2), \ \alpha_t \sim \mathcal{N}(0, \sigma_t^2) \tag{6}$$

Equation (4) is the individual-level regression: i indicates a country, and t indicates a year. The subscript of parameters $\alpha_{j[it]}$ and $\beta_{j[it]}$ denotes whether the observation of country i at time t is a democracy ($j[it]$=1)or autocracy ($j[it]$=0). That is, $\alpha_{j[it]} = \alpha_1/\alpha_0$ and $\beta_{j[it]} = \beta_1/\beta_0$ are regime-specific intercepts and coefficients.

Equations (5) and (6) are the specifications of varying intercepts and regime-specific coefficient, reflecting heterogeneity in multiple dimensions of time, unit, and regime type. As shown in Equation (5), β_j consists of a shared part, β, by both regimes and a varying part, $\epsilon_j \sim \mathcal{N}(0, \sigma_{2j}^2)$, that is different across regimes. As opposed to a subsample analysis, the multilevel model admits the fact that different regimes coexist in a larger population and may share some common attributes that lead to a shared loan-to-transparency mechanism, β. The heterogeneous effect across regimes is captured by the regime-specific random effect ϵ_j. The regime-specific intercept, α_j, captures the impact of regime heterogeneity on the outcome. We can see that, in multilevel modeling, regime type is treated as a macro-institutional context that shapes and moderates the mechanism through

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which loans affect transparency.

There are several advantages of applying multilevel modeling to test our hypotheses. First, compared with fixed effects models, the multilevel model can include more than two-way fixed effects. Its model specification and estimation strategy allow it to have unit-invariant or time-invariant covariates at the same time with fixed effects. Second, multilevel modeling is more efficient than split-sample (democracy or autocracy) regressions, because it can borrow information across groups (Gelman and Hill, 2006). Third, as opposed to regressions with an interactive term (i.e., $regime * loan.IO$), multilevel modeling treats regime type as part of the macro-level institutional environment and the conditioning goes from the macro context to micro behavior ($loan.IO|regime$), whereas in an interactive term, the components have exchangeable positions and the conditioning goes both ways, $\beta_{loan.IO}|regime$ and $\beta_{regime}|loan.IO$, but the latter is difficult to interpret.[12]

We conduct multilevel analyses by estimating and comparing three different specifications, including models with an invariant $\beta_{loan.IO}$ across regimes (M1), models with regime-specific coefficients $\beta_{loan.IO}|regime$ (M2), and models with an interactive term $regime * loan.IO$ (M3). The results are largely robust to alternative measures of the key variables and various methods.

5   Results

5.1   Matching

We adjust carry-over effects for three years ($L = 3$) in the treatment history. The choice of the value of L is arbitrary, and we have to balance the trade-off between the size of matched set and the length of matched treatment history: the size of matched set decreases with a larger L, and an L larger than 3 leads to much smaller size of matched set based on our sample. We set $F = 8$ to take a relatively long time horizon, since the size of matched set is not too sensitive to the choice

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[12]See Chaudoin, Milner, and Pang (2015) for a more detailed discussion about the differences between interaction terms and varying-coefficients.

of F. Only those observations that change treatment status less than F years before the end of the sample period are excluded.[13] We use the Covariate Balancing Propensity method to correct for the selection bias and improve balancing; alternative methods such as propensity score weighting and Mahalanobis matching generate similar results.
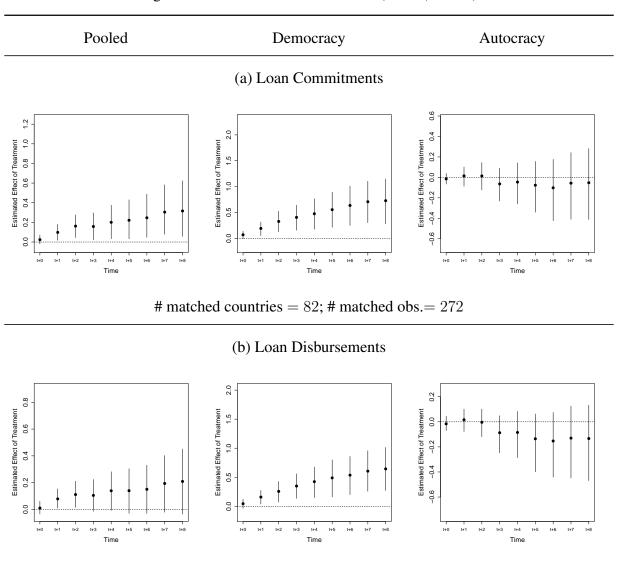
Figures 4 and 5 report the estimates and 95% confidence intervals of ATTs of loan commitments and disbursements from t_0 to t_8, where the effect at t_0 is the instantaneous effect. We also report the number of matched countries and matched observations in the figures. The first column displays the results when pooling all countries; the second and third columns are the ATTs of democracies and autocracies, respectively.

The effects of IMF loan commitments (top panel) and disbursements (bottom panel) have similar patterns (Figure 4). Column (1) suggests that IMF loan commitments and disbursements both significantly increase the level of transparency of countries that participate in loan programs. The significant positive effect lasts for at least eight years after receiving loan commitments and increases over time, whereas the effects of IMF loan disbursements reach conventional thresholds of significance only in the short-term. These estimates suggest that pressure to provide more and better data is most acute at the time of the loan, but the influence of the IMF over data collection becomes more varied and uncertain (not statistically significant) after the initial loan disbursement. The magnitude of the point estimate of the long-term (t+8) effect in the top panel of column 1 ($\approx$ 0.3 on the HRV index scale) is approximately equal to $\frac{1}{8}$ of a standard deviation in index values.

Columns (2) and (3) report the ATTs of IMF loans on transparency across regimes. The figures distinctly indicate that the effects are exclusively observed in democracies. Both loan commitments and disbursements significantly enhance transparency in democracies, with the effects being both enduring and increasing. However, it appears that IMF loans do not have any reliable effect on improvements in transparency in autocracies.

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[13]In the Supporting Information, we set $F = 4$ (see Figures A1 and A2) and also set $L = 5$ (see Figures A3 and A4) ; the results are similar though the matched countries and matched observations are modestly different.

Figure 4: IMF Loans: Causal Effects ($L = 3, F = 8$)

	Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 82$; # matched obs.$= 272$

(b) Loan Disbursements

matched countries $= 81$; # matched obs.$= 253$
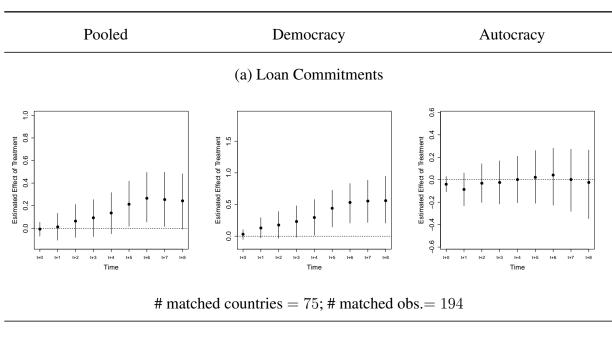
Turning to the WB, we note that the treatment assignment patterns of its loans are significantly different from those of IMF: the WB tends to continuously finance countries over a longer time horizon. Figure 5 estimates the effect of WB loan commitments (top panel) and disbursements (bottom panel) on transparency up to eight years after the loan. Loan commitments from the WB have a long-term effect on the level of transparency of recipient countries. The effect develops gradually and becomes statistically significant in the fifth year of the loan. However, there is no discernible significant effect of WB loan disbursements, and the point estimates appear to trend
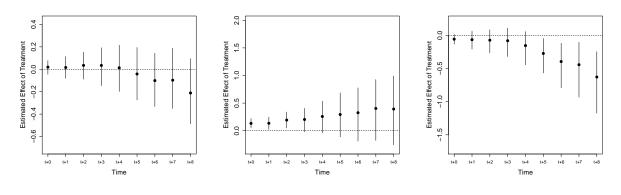
negatively with the passage of time.

When examining the distinct effects of the WB on democracies and autocracies, it becomes evident that the effect is exclusive to democracies, mirroring the pattern seen with IMF loans. In democracies, there is a long-term effect of WB loan commitments and a short-term effect of WB loan disbursements. However, in non-democracies, WB loan commitments show no significant effect. Surprisingly, economic transparency in non-democracies even appears to decrease after five years of receiving WB loans.

Figure 5: WB Loans: Causal Effects($L = 3, F = 8$)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 75$; # matched obs.$= 194$

(b) Loan Disbursements

matched countries $= 69$; # matched obs.$= 183$

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5.2 Multilevel regression analysis

We complement the matching approach with regression analysis. We do not interpret the regression coefficients here as "causal effects" because the two-way fixed effects linear regression and its variants (such as the multilevel analysis that we use) are only equivalent to the difference-in-differences estimator "under the simplest setting with two groups and two time periods."[14] We can, however, test the association between loan amounts and the level of transparency with the *whole sample* rather than a small matched subset, while controlling for covariates.

All models include year-specific, country-specific, and regime-specific intercepts. For the dependent variables, we use both loan size and a binary loan indicator (for commitments and disbursements, respectively). The information-based criteria for model selection (AIC, BIC, and log likelihood) all indicate a preference for the models with a constant coefficient across regimes (M1). That is, the regression analysis suggests that BWIs' loans do not impact the data disclosure of democratic governments differently from how they affect autocracies.

Figure 6 reports the estimates and 95% confidence intervals of the association between BWIs' loan amounts and transparency based on the three different specifications. Different model specifications generally agree with each other, and suggest a positive association, broadly with the previous analysis, although not without some nuances.

Interestingly, the estimate profiles are very similar when coding the explanatory variables as discrete; they differ only in magnitude and turning "on" or "off" the treatment is associated with an expected change of transparency by about about 0.06 to 0.07 units on the HRV scale for WB and 0.04 to 0.06 points for IMF loans. Given that the preponderance of the variance in loan size is between country-years that receive a commitment/disbursement and those that do not (and so are coded as zero), we focus our discussion on the binary controls. The linearity assumption underlying the (quasi-)continuous treatment may be strong in this instance.

The point estimates on the binary indicators in Figure 6 (b) are substantively small. A movement of 0.06 units on the HRV index scale is comparable to the annual change in transparency

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[14]See Imai and Kim (2021, p.405).

scores witnessed in Vietnam during the late-1980s and early-1990s, following the reforms of the 1986 Party Congress. However, recall that our specifications include a lag of transparency (LDV) in the estimating equation, implying a dynamic relationship in which the marginal effect of a loan evolves geometrically over time (Beck and Katz, 2011). The coefficient on the LDV, as reported in Table 2 is substantively large (approximately 0.97 in all specifications). Were the loan dummy to switch from a value of zero to that of one permanently, this implies a long-run equilibrium effect roughly 30 times the size of the point estimate, a 1.8 point shift in transparency scores, or 0.78 standard deviations.

BWI lending (particularly IMF lending) often doesn't follow this pattern (see Supplementary Information S-1), and so such an interpretation involves extrapolation from the model beyond the coverage of the data and should be taken with a grain of salt. However, the dynamics of the model do imply that changes in transparency associated with BWI lending are persistent and grow over time, as is also consistent with the pattern *PanelMatch* discovers for the ATT in democracies.[15] Vietnam witnessed such a pattern of consistent liberalization over the decade following the 1986 Party Congress and—while the increase in transparency year-to-year was small, the cumulative rise reflected one of the more pronounced examples of autocratic liberalization according to the HRV index.

Among the regression models, the estimates based on M1 (the pooled effects) are roughly the average of the regime-specific effects based on models with regime-varying coefficients (M2.auto and M2.demo) or on models with an interactive term (M3.auto and M3.demo). M3 suggests bigger regime-differences than M2 does, but the 95% confidence intervals of regime-specific estimates are largely overlapping in both models, confirming what is suggested by model comparison with information-based criteria—the association is not different across regimes. Furthermore, M3 finds neither IMF loan commitments nor IMF disbursements have a significant association with the economic transparency of democracies, either in terms their size or dichotomous intervention. M1 and M2 suggest that pooled and regime-specific effects are all statistically significant, whereas M2,

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[15]Though, the coefficients from the multilevel data imply a smaller marginal effect than the ATT estimated by *PanelMatch*, suggesting that selection bias may an issue and the ATT and average treatment effect substantially diverge.

the model with an interactive term suggests neither IMF disbursements nor IMF commitments have a significant effect on democracies.
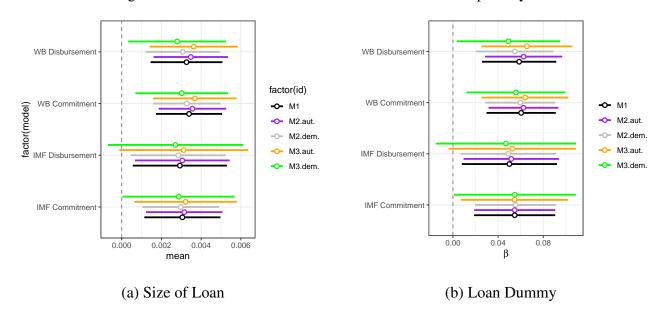
Figure 6: Estimated Coefficients of BWI Loans on Transparency

(a) Size of Loan

(b) Loan Dummy

Note: Coefficients from the multilevel models. The left panel considers the size of a loan (at the logarithmic scale) as the independent variable; the right panel uses a dichotomous indicator for a country-year with or without a loan.

Table 2 reports the estimated coefficients associated with the control variables based on the best model with a pooled effect of BWIs' loans, using the size of BWI loans (M1 in Figure 6(a)).[16]

As noted above, we find strong autocorrelation in the outcome variable, the HRV index, which is greater than 0.95 after we control for time-varying covariates.[17] The lagged transparency level explains most of the variation in the dependent variables, with $R^2 = 0.970$ in the simple regression on transparency level with the lagged level. The lagged dependent variable may be absorbing the effects of weaker factors, which is the reason that most of our control variables do not have a

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[16]For M1 using BWI loan dummies, M2 and M3, the results are reported in the Appendix as Tables A1, A2, A3, A4, and A5.

[17]Serial correlation is built into the estimate of this variable (Hollyer, Rosendorff, and Vreeland, 2014). Our mixed-effect/multilevel models are estimated using restricted maximum likelihood (Bates et al., 2015). Given concerns about including the lagged dependent-variable along with time- and country-varying intercepts, we consider models without these terms, reported in supplemental Tables S5 and S6. The qualitative conclusions from these models are the same as in our baseline results.

Table 2: M1: Loan Commitment/Disbursement Size and Transparency

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	-0.524^{***}	-0.512^{***}	-0.544^{***}	-0.563^{***}
	(0.115)	(0.115)	(0.115)	(0.116)
Lagged Transparancy	0.968^{***}	0.968^{***}	0.966^{***}	0.966^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Democracy	0.047^{**}	0.047^{**}	0.042^{*}	0.044^{**}
	(0.017)	(0.017)	(0.017)	(0.017)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	-0.008	-0.009	-0.008	-0.012
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.015	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.303	0.303	0.242	0.258
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.282	0.282	0.235	0.251
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	-0.275	-0.275	-0.218	-0.234
	(0.188)	(0.188)	(0.189)	(0.188)
Signed BITs	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.043	0.045	0.036	0.040
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.044^{*}	0.042^{*}	0.044^{*}	0.046^{*}
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.182^{***}	0.180^{***}	0.191^{***}	0.194^{***}
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	-0.006	-0.008	0.003	0.005
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	-0.011^{**}	-0.011^{**}	-0.010^{**}	-0.010^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	-0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3412.766	3416.672	3406.568	3410.049
BIC	3543.586	3547.492	3537.388	3540.869
Log Likelihood	-1685.383	-1687.336	-1682.284	-1684.025
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: Regime	2	2	2	2

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Multilevel regression for pooled sample.

statistically significant associations with transparency. In the models with an invariant coefficient on loans across regime types, we are able to include the variable *Democracy* as a control variable. As expected, being democratic is positively associated with transparency.[18] There are two region-indicators (Asia and Europe) that are significantly associated with a higher-level of transparency, compared to the baseline category of Africa.

Substantively, the multilevel analysis produces some different findings compared to the results from the matching/causal inference approach. While the causal analysis suggests that the effect is, in general, stronger on democracies than on autocracies, the multilevel analysis finds no significant difference across regimes. Moreover, the multilevel analysis finds that the association between WB loans and transparency is significant for both disbursements and commitments, whereas the matching/causal inference does not estimate much effect of WB disbursements. Also, regressions weakly suggest that IMF disbursements and commitments may not be significantly associated with an increase of economic transparency in democracies, whereas *PanelMatch* finds both long-run and short-run effects of IMF loans on democracies. The consistent finding across the methods is a positive and statistically significant association between BWIs' loans and the improvement of the level of economic transparency in developing countries.

6 Conclusion

The statistics made available by the IMF and the WB shape much of the research and policy discussions among international affairs professionals. We show that loans from these institutions increase the amount of available economic data provided by recipient governments.

Our results are corroborated by two methods—the *PanelMatch* approach to causal inference of Imai, Kim, and Wang (2021) and multilevel regression analysis. *PanelMatch* enables us to estimate causal effects with a high degree of internal validity, but potentially at the expense of external validity due to a lack of matching observations. The complimentary multilevel modeling

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[18]In models with regime-specific coefficients, *Democracy* cannot be included as a control variable because it serves as a group indicator.

approach does not estimate causal effects, but enables us to estimate heterogeneous associations of loans across political regimes with a varying coefficients and controls for unobserved heterogeneity with country-, year-, and regime-varying intercepts.

Both approaches confirm a positive association between BWI loans and increased transparency. *PanelMatch* suggests that the effect for democracies is causal. The results suggest that the effect comes through capacity building—the loans and technical advice—rather than through coerced policy conditionality. While our evidence of mechanisms is speculative, this pattern is consistent with the more robust positive relationship between BWI lending and transparency in democracies.

Other forms of development assistance—from other multilateral organizations and from bilateral donor countries—may also improve rates of data disclosure by democratic governments. We argue that BWI loans help democracies overcome capacity constraints, but BWIs can help governments in this regard through two potential mechanisms: funding and technical advice. If democracies only require funding, then a wide range of development assistance may improve economic transparency under democracy. But if the key to success is technical advice, then BWI assistance may outshine other providers. This question may rise in importance as more developing countries consider borrowing from new organizations, such as the AIIB (Qian, Vreeland, and Zhao, 2023).

Alternative facets of transparency under democracy may also be enhanced by international organizations—for example, certain human rights organizations require states to self-certify rights compliance. Future research might examine a broader range of international organizations and measures of transparency.

The results for autocratic regimes were inconclusive; further research into the varieties of autocracy or other institutional features may yield insights. As a preliminary step in this direction, we include estimates of the ATT varying across six definitions of regime-type {parliamentary democracy, presidential democracy, semi-presidential democracy, military autocracy, civilian autocracy, monarchy} in the supplementary material. These produce some evidence that BWI lending has a negative ATT in military dictatorships, though these results should be treated as speculative given the sample size.

While the World Bank, IMF, and other international organizations have implemented reporting practices that discourage the publication of low-quality data, regular updates and corrections to pre-existing data suggest that data quality varies systematically across countries with different levels of economic development and different political institutions. Future research might consider whether more frequent borrowing from the BWIs results in governments producing data that are less likely to require corrections over time.

The lending activities of the BWIs improve the production and dissemination of economic information by the democratic governments that borrow from them. BWI lending has enhanced the collection and dissemination of data, a vital resource for investors, policymakers, and scholars, who use them to make better decisions for economic development.

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Online Appendix

This appendix presents additional information for the matching/causal inference and multilevel analysis estimations. Tables and figures are labeled with prefix A. Further information is presented below in a separate document (Supplementary Information). Tables and figures there are labeled with prefix S.

Several checks of the mechanism are explored in the Supplementary Information. First, we vary F and L to see whether the results in the main analysis substantively change. Figures A1 and A2 show the estimates by setting varying $F = 4$. In general, the findings are similar to those in the main analysis. Figures A3 and A4 depict the results by setting $L = 5$. The estimates are also similar to those in the main analysis. But with a smaller set of matched observations, the error bounds are larger, leading to no significant effects except the negative impact of WB disbursement on autocracies.

A Multilevel Analysis

Tables A1 to A5 report the estimates and standard errors of the control variables based on multilevel models with pooled effects, regime-specific coefficients, and interactive terms of regime and loans, using loan size or loan dummy as dependent variable.

B Robustness Checking: Varying Lags and Leads

We vary the length of treatment history for matching, denoted as L, and the number of post-treatment periods, denoted as F, to assess the robustness of the findings from the main analysis. However, no substantively noticeable differences are observed when F and L vary modestly.

Table A1: M1: Estimated Coeffcients of Control Variables (Loan Dummy)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.528***	−0.515***	−0.568***	−0.584***
	(0.115)	(0.115)	(0.116)	(0.118)
Lagged Transparancy	0.968***	0.968***	0.966***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Democracy	0.047**	0.047**	0.042*	0.044**
	(0.017)	(0.017)	(0.017)	(0.017)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.008	−0.010	−0.008	−0.011
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.016	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.304	0.305	0.251	0.265
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.283	0.283	0.242	0.256
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	−0.275	−0.277	−0.225	−0.239
	(0.188)	(0.188)	(0.188)	(0.188)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.044	0.046	0.037	0.040
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.044*	0.042*	0.045*	0.046*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.183***	0.180***	0.191***	0.194***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.006	−0.008	0.003	0.004
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3413.604	3417.131	3407.683	3410.287
BIC	3544.424	3547.951	3538.502	3541.107
Log Likelihood	−1685.802	−1687.566	−1682.841	−1684.144
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Multilevel regression for pooled sample.

Table A2: M2: Estimated Coeffcients of Control Variables (Loan Size)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.503***	−0.492***	−0.528***	−0.545***
	(0.117)	(0.117)	(0.117)	(0.118)
IMF Commitment	0.003**			
	(0.001)			
IMF Disbursement		0.003*		
		(0.001)		
WB Commitment			0.003***	
			(0.001)	
WB Disbursement				0.003***
				(0.001)
Lagged Transparency	0.968***	0.969***	0.966***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.006	−0.007	−0.005	−0.009
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.015	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.309	0.310	0.244	0.261
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.289	0.289	0.238	0.254
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	−0.281	−0.282	−0.220	−0.236
	(0.188)	(0.188)	(0.189)	(0.188)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.047	0.049	0.040	0.045
	(0.027)	(0.027)	(0.027)	(0.026)
Asia	0.045*	0.043*	0.046*	0.048*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.186***	0.184***	0.195***	0.198***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.002	−0.005	0.007	0.008
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3418.801	3422.703	3412.263	3415.751
BIC	3555.850	3559.753	3549.312	3552.800
Log Likelihood	−1687.401	−1689.352	−1684.132	−1685.875
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Multilevel regression for pooled sample.

Table A3: M2: Estimated Coeffcients of Control Variables (Loan Dummy)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.508***	−0.495***	−0.552***	−0.565***
	(0.117)	(0.117)	(0.118)	(0.119)
IMF Commitment	0.055**			
	(0.018)			
IMF Disbursement		0.050*		
		(0.022)		
WB Commitment			0.061***	
			(0.016)	
WB Disbursement				0.059***
				(0.017)
Lagged Transparancy	0.968***	0.969***	0.966***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.006	−0.007	−0.006	−0.009
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.016	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.311	0.312	0.256	0.268
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.290	0.290	0.248	0.259
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	−0.283	−0.283	−0.230	−0.242
	(0.188)	(0.188)	(0.188)	(0.188)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.047	0.050	0.041	0.045
	(0.027)	(0.027)	(0.027)	(0.026)
Asia	0.045*	0.043*	0.046*	0.048*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.187***	0.184***	0.196***	0.198***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.002	−0.005	0.007	0.007
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3419.648	3423.165	3413.389	3416.000
BIC	3556.697	3560.214	3550.438	3553.050
Log Likelihood	−1687.824	−1689.582	−1684.694	−1686.000
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Table A4: M3: Estimated Coeffcients of Control Variables (Loan Size)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.523***	−0.511***	−0.547***	−0.566***
	(0.115)	(0.115)	(0.116)	(0.117)
Democracy	0.048**	0.048**	0.050*	0.054*
	(0.018)	(0.017)	(0.024)	(0.025)
IMF Commitment	0.003*			
	(0.001)			
Democracy × IMF Commitment	−0.000			
	(0.002)			
IMF Disbursement		0.003		
		(0.002)		
Democracy × IMF Disbursement		−0.000		
		(0.002)		
WB Commitment			0.004***	
			(0.001)	
Democracy × WB Commitment			−0.001	
			(0.001)	
WB Disbursement				0.004**
				(0.001)
Democracy × WB Disbursement				−0.001
				(0.002)
Lagged Transparancy	0.968***	0.968***	0.965***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.009	−0.010	−0.008	−0.011
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.015	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.302	0.302	0.233	0.249
	(0.189)	(0.189)	(0.190)	(0.190)
GDP pc	0.281	0.281	0.226	0.242
	(0.188)	(0.188)	(0.189)	(0.189)
GDP	−0.274	−0.274	−0.209	−0.225
	(0.188)	(0.188)	(0.190)	(0.189)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.043	0.046	0.037	0.042
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.044*	0.042*	0.046*	0.048*
	(0.020)	(0.020)	(0.021)	(0.021)
Europe	0.183***	0.180***	0.191***	0.193***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.006	−0.009	0.002	0.003
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3414.735	3418.642	3408.368	3411.741
BIC	3551.784	3555.691	3545.417	3548.791
Log Likelihood	−1685.367	−1687.321	−1682.184	−1683.871
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Table A5: M3: Estimated Coeffcients of Control Variables (Loan Dummy)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.528***	−0.515***	−0.570***	−0.586***
	(0.115)	(0.115)	(0.116)	(0.118)
Democracy	0.047**	0.048**	0.048*	0.055*
	(0.018)	(0.017)	(0.024)	(0.025)
IMF Commitment	0.055*			
	(0.024)			
Democracy × IMF Commitment	0.000			
	(0.036)			
IMF Disbursement		0.052		
		(0.029)		
Democracy × IMF Disbursement		−0.006		
		(0.042)		
WB Commitment			0.064**	
			(0.020)	
Democracy × WB Commitment			−0.008	
			(0.028)	
WB Disbursement				0.066**
				(0.020)
Democracy × WB Disbursement				−0.016
				(0.028)
Lagged Transparancy	0.968***	0.968***	0.966***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.008	−0.010	−0.008	−0.011
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.016	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
Population	0.304	0.304	0.245	0.256
	(0.189)	(0.189)	(0.190)	(0.190)
GDP pc	0.283	0.283	0.236	0.247
	(0.188)	(0.188)	(0.189)	(0.189)
GDP	−0.275	−0.276	−0.220	−0.230
	(0.188)	(0.188)	(0.189)	(0.189)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.044	0.046	0.038	0.043
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.044*	0.042*	0.045*	0.048*
	(0.020)	(0.020)	(0.021)	(0.021)
Europe	0.183***	0.181***	0.191***	0.193***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.006	−0.008	0.002	0.003
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3415.604	3419.114	3409.596	3411.948
BIC	3552.654	3556.163	3546.645	3548.997
Log Likelihood	−1685.802	−1687.557	−1682.798	−1683.974
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Figure A1: IMF Loans: Causal Effects ($L = 3, F = 4$)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 85$; # matched obs.$= 316$

(b) Loan Disbursements

matched countries $= 81$; # matched obs.$= 288$
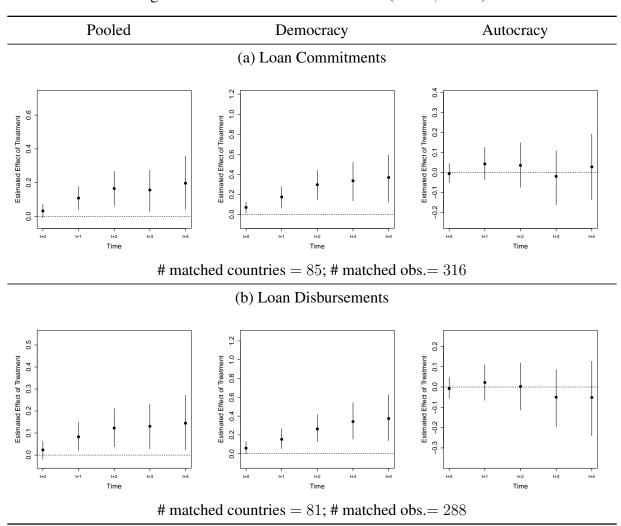
Figure A2: WB Loans: Causal Effects($L = 3, F = 4$)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 81$; # matched obs.$= 226$

(b) Loan Disbursements

matched countries $= 72$; # matched obs.$= 205$

Figure A3: IMF Loans: Causal Effects ($L = 5, F = 8$)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 80$; # matched obs.$= 251$

(b) Loan Disbursements

matched countries $= 77$; # matched obs.$= 221$

Figure A4: WB Loans: Causal Effects($L = 5, F = 8$)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 68$; # matched obs.$= 199$

(b) Loan Disbursements

matched countries $= 48$; # matched obs.$= 168$

Online Supplementary Information

Table of contents

Data Structure

We report the data structure of the sample in Figure S1 and Figure S2. Figure S3 displays how loan commitments and disbursements are distributed according to the transparency level of recipient countries.

Figure S1: Treatment Assignment (IMF Loans)

Both Regimes	Democracy	Autocracy

(a) Commitment

(b) Disbursement
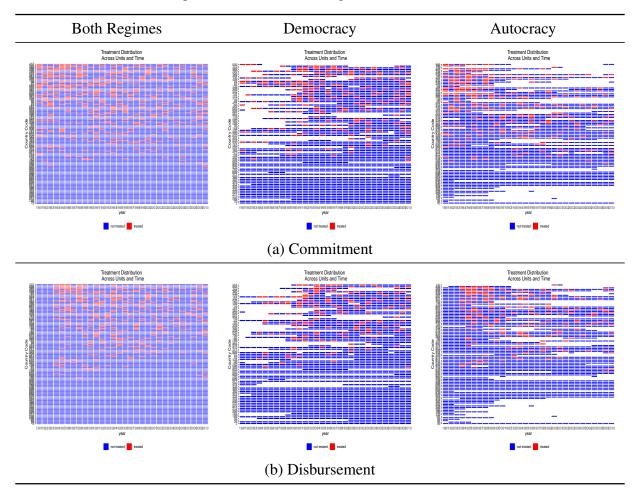
Figure S2: Treatment Assignment (WB Loans)

Both Regimes	Democracy	Autocracy

(a) Commitment

(b) Disbursement

Figure S3: Loans and Transparency

Both Regimes	Democracy	Autocracy

(a) IMF Loan Commitments

(a) IMF Loan Disbursements
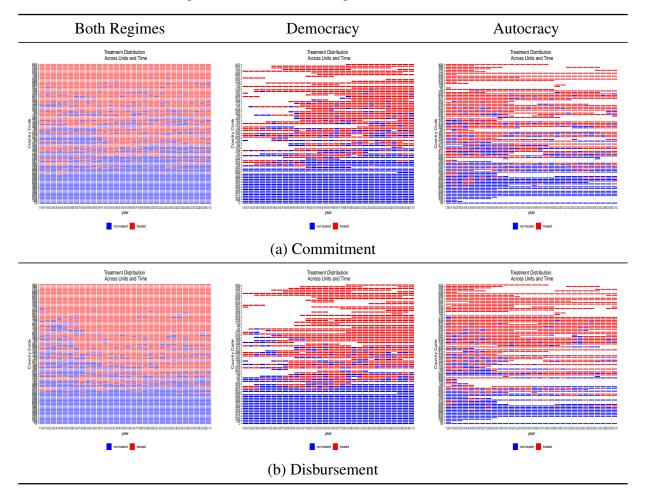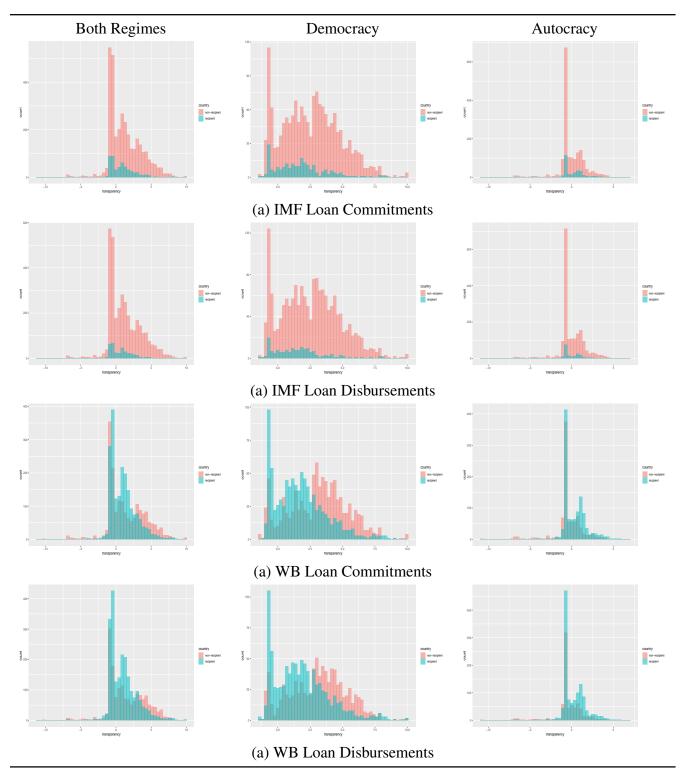

(a) WB Loan Commitments

(a) WB Loan Disbursements

Checks on Causal Mechanism

We conducted several additional analyses to explore the causal mechanism. First, instead of employing a dichotomous measure of regime type, we examined how the effects of BWI loans varied across six different categories of regimes. Figures S4, S5, S6, and S7 illustrate the regime-specific effects using the 6-category regime variable as a moderator. The general finding confirms that the effects are concentrated in democracies, and non-democracies are barely affected by BWI loans. But there are also some interesting findings in this analysis:

- Regarding IMF loan commitments, their primary effect is observed in democracies, particularly in mixed (semi-presidential) democracies. There is an almost significant positive effect on civilian dictatorship in the autocracy domain. Interestingly, loan commitments exhibit significant negative effects on military dictatorship, and these effects are longer-term. The confidence intervals (CIs) of the effects on royal dictatorship cannot be accurately estimated due to the limited matched observations, making inference challenging.

- Regarding IMF loan disbursements, we observe a very similar pattern to that of IMF loan commitments.

- Concerning the effect of WB commitments, we note that the impact is primarily observed in mixed (semi-presidential) democracies and presidential democracies. No discernible effects on autocracies are found, except for a short-term negative effect on civilian dictatorship. Again, CIs of the effects on royal dictatorship cannot be accurately estimated.

- In conclusion, the estimated effects of WB loan disbursements are perplexing and challenging to interpret. We observe short-term, significant, positive effects on mixed (semi-presidential) democracies and presidential democracies, almost significant negative effects on parliamentary democracies, and significant, shorter- and longer-term effects on civilian dictatorship.

Figure S4: IMF Loan Commitments: Regime Categories ($L = 3, F = 8$)

Parliamentary Democracy

Mixed (semiâpresidential) democracy

Presidential Democracy

(b) Loan Disbursements

Civilian Authoritariamism

Military Authoritariamism

Royal Authoritariamism
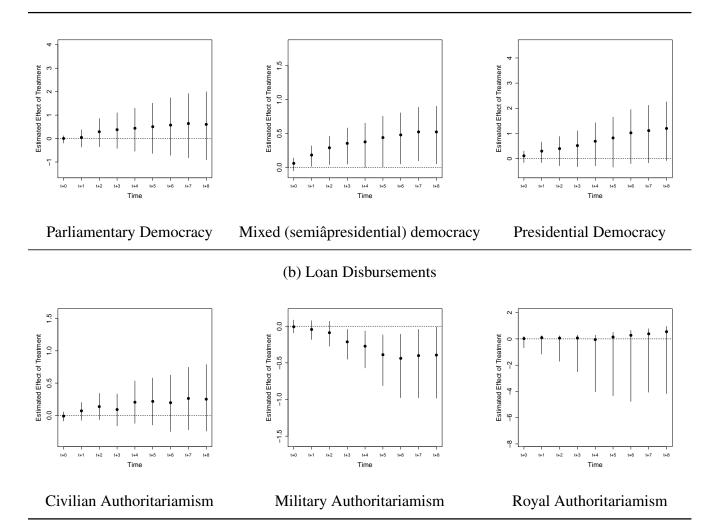
Figure S5: IMF Loan Disbursements: Regime Categories ($L = 3, F = 8$)

Parliamentary Democracy | Mixed (semiâpresidential) democracy | Presidential Democracy

(b) Loan Disbursements

Civilian Authoritariamism | Military Authoritariamism | Royal Authoritariamism
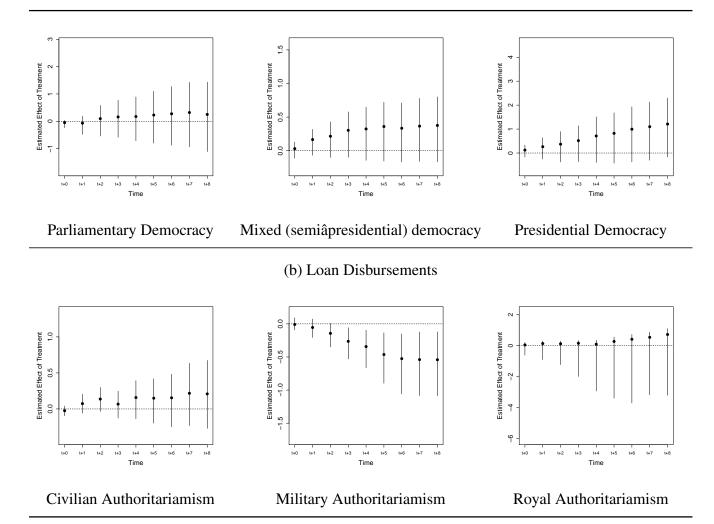
Figure S6: WB Loan Commitments: Regime Categories ($L = 3, F = 8$)

Parliamentary Democracy   Mixed (semiâpresidential) democracy   Presidential Democracy

(b) Loan Disbursements

Civilian Authoritariamism   Military Authoritariamism   Royal Authoritariamism
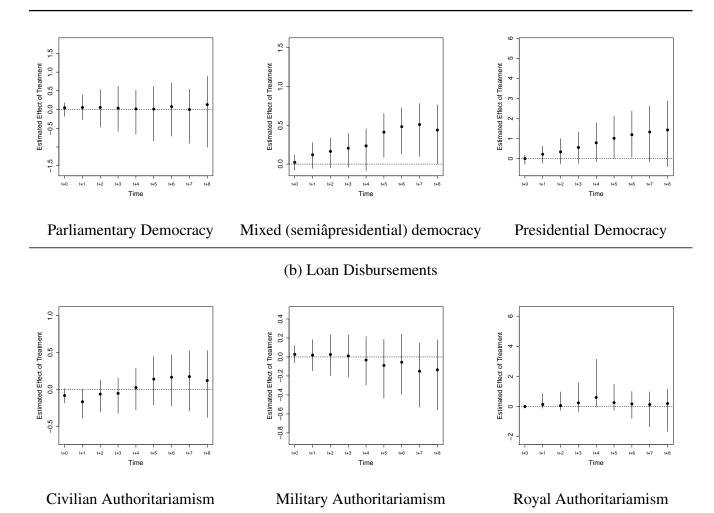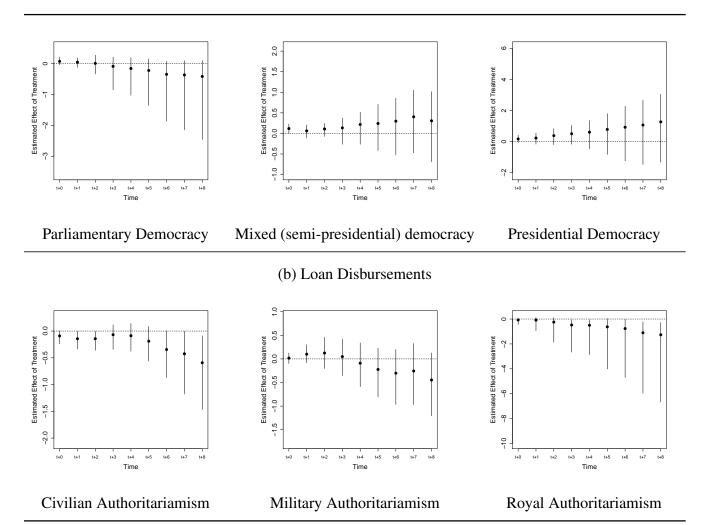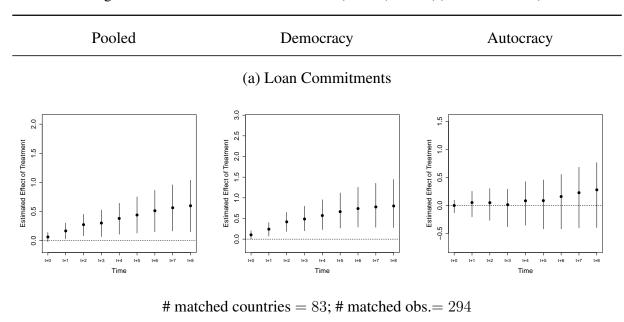
Figure S7: WB Loan Disbursements: Regime Categories ($L = 3, F = 8$)

Parliamentary Democracy · Mixed (semi-presidential) democracy · Presidential Democracy

(b) Loan Disbursements

Civilian Authoritariamism · Military Authoritariamism · Royal Authoritariamism

Secondly, we compare the ATTs of BWI loans on countries above or below the median level of transparency in the year before they are treated. The analysis uses $GDP\,pc > median(GDP\,pc)" \times democracy$ as the moderator in causal inference. Figures S8, S9, S10, S11 report the estimates. We find that overall, BWI loans increase transparency in more developed recipients, but barely have significant effects on less developed ones.

Figure S8: IMF Loans: Causal Effects ($L = 3, F = 8$)(Above Median)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 83$; # matched obs.$= 294$

(b) Loan Disbursements

matched countries $= 81$; # matched obs.$= 253$
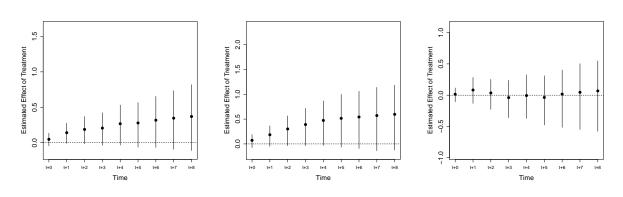
Figure S9: IMF Loans: Causal Effects ($L = 3, F = 8$)(Below Median)

	Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries = 83; # matched obs.= 294

(b) Loan Disbursements

matched countries = 81; # matched obs.= 253
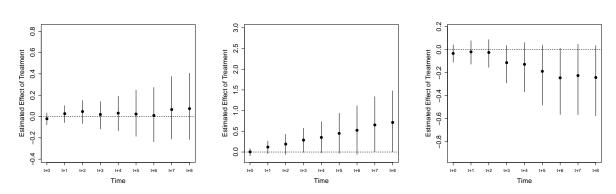
Figure S10: WB Loans: Causal Effects($L = 3, F = 8$) (Above Median)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 78$; # matched obs.$= 205$

(b) Loan Disbursements

matched countries $= 71$; # matched obs.$= 194$
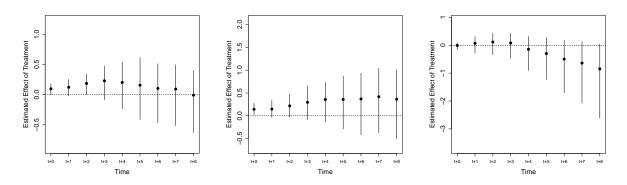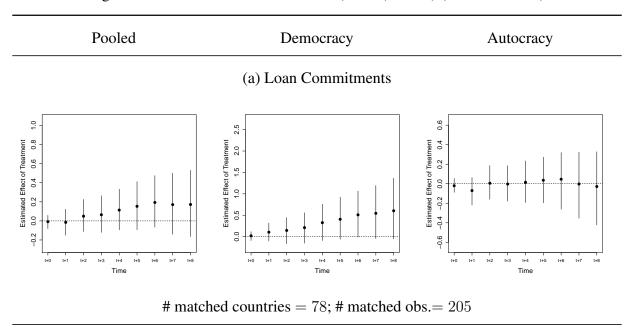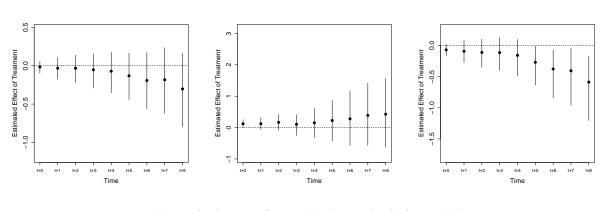
Figure S11: WB Loans: Causal Effects($L = 3, F = 8$) (Below Median)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $=$ 78; # matched obs.$=$ 205

(b) Loan Disbursements
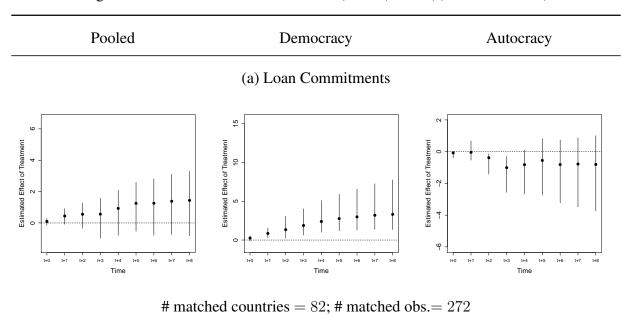
matched countries $=$ 71; # matched obs.$=$ 194

Finally, we compare the effects of loans on countries that are United Nations Security Council (UNSC) member states with those that are not. This analysis uses "UNSC member" $\times$ democracy indicator as the moderator in *PanelMatch* function. Figures S12, S13, S14, and S15 depict the results. The estimates suggest that: 1) BWI loans exhibit stronger positive effects on non-UNSC member states than on members; 2) The positive effects are exclusively observed in democracies; 3) We observe negative effects of IMF loans on autocratic UNSC member states.

Figure S12: IMF Loans: Causal Effects ($L = 3, F = 8$)(UNSC Member)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 82$; # matched obs.$= 272$

(b) Loan Disbursements

matched countries $= 81$; # matched obs.$= 253$
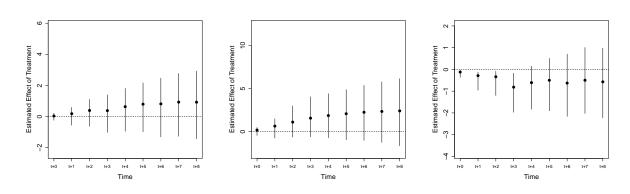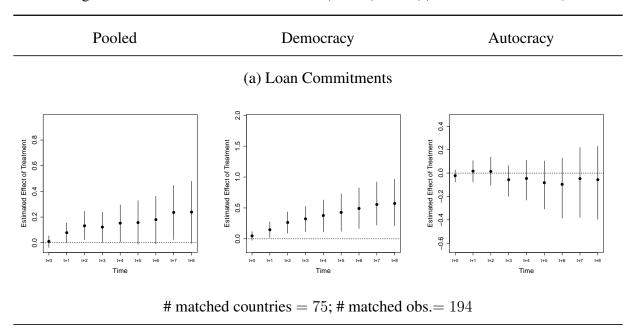
Figure S13: IMF Loans: Causal Effects ($L = 3, F = 8$)(UNSC Non-Member)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries = 75; # matched obs.= 194

(b) Loan Disbursements

matched countries = 69; # matched obs.= 183
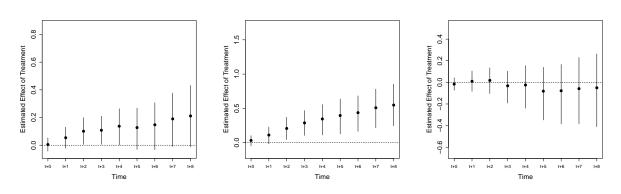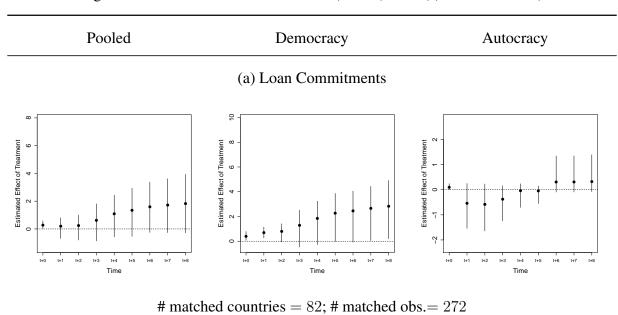
Figure S14: WB Loans: Causal Effects ($L = 3, F = 8$)(UNSC Member)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 82$; # matched obs.$= 272$

(b) Loan Disbursements

matched countries $= 81$; # matched obs.$= 253$
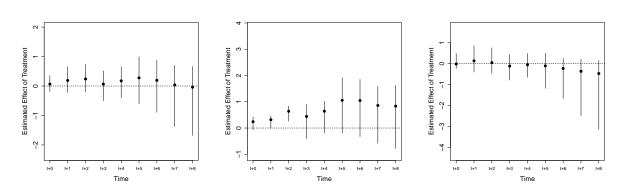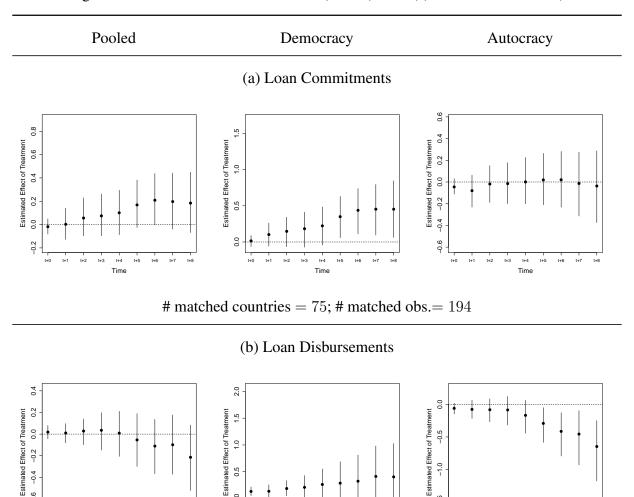
Figure S15: WB Loans: Causal Effects ($L = 3, F = 8$)(UNSC Non-Member)

Pooled	Democracy	Autocracy

(a) Loan Commitments

matched countries $= 75$; # matched obs.$= 194$

(b) Loan Disbursements

matched countries $= 69$; # matched obs.$= 183$

Additional Regression Analyses

We performed additional multilevel analyses, including those reported in the previous section, and utilized loan per capita as an alternative measure of the outcome variable, along with simple linear regressions. The findings are robust across all analyses and consistently indicate a positive and significant effect of BWI loans on economic transparency.

Table S1: Varying Effect of Size of BWI Loans on Level of Development

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.278	−0.266	−0.200	−0.041
	(0.213)	(0.212)	(0.222)	(0.229)
GDP pc	0.525	0.521	0.462	0.437
	(0.286)	(0.287)	(0.286)	(0.286)
IMF Commitment	−0.020			
	(0.012)			
GDP pc × IMF Commitment	0.003*			
	(0.001)			
IMF Disbursement		−0.018		
		(0.014)		
GDP pc× IMF Disbursement		0.003		
		(0.002)		
WB Commitment			−0.018	
			(0.009)	
GDP pc× WB Commitment			0.003*	
			(0.001)	
WB Disbursement				−0.035***
				(0.010)
GDP pc× WB Disbursement				0.004***
				(0.001)
Lagged Transparancy	0.951***	0.952***	0.949***	0.946***
	(0.007)	(0.007)	(0.007)	(0.007)
Trade	−0.001	−0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	0.069	0.068	0.065	0.058
	(0.052)	(0.052)	(0.052)	(0.052)
UNSC Member	0.014	0.015	0.007	0.005
	(0.034)	(0.034)	(0.034)	(0.034)
Population	0.538	0.533	0.477	0.477
	(0.290)	(0.290)	(0.291)	(0.290)
GDP	−0.519	−0.516	−0.459	−0.454
	(0.287)	(0.288)	(0.288)	(0.287)
Signed BITs	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.045	0.055	0.001	−0.024
	(0.048)	(0.048)	(0.051)	(0.051)
Asia	0.055	0.056	0.055	0.049
	(0.044)	(0.044)	(0.044)	(0.044)
Europe	0.244***	0.248***	0.237***	0.241***
	(0.050)	(0.050)	(0.051)	(0.050)
Oceania	−0.005	−0.007	0.010	0.011
	(0.057)	(0.057)	(0.057)	(0.057)
Political Instability	−0.006	−0.006	−0.006	−0.006
	(0.007)	(0.007)	(0.007)	(0.007)
Geo-Distance	−0.001	−0.000	−0.004	−0.005
	(0.005)	(0.005)	(0.005)	(0.005)
AIC	1856.884	1860.000	1849.984	1840.730
BIC	1972.150	1975.266	1965.250	1955.996
Log Likelihood	−907.442	−909.000	−903.992	−899.365
Num. obs.	1788	1788	1788	1788
Num. groups: ccode	83	83	83	83
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Multilevel regression for pooled sample.

Table S2: Varying Effect of BWI Loan Dummies on Level of Development

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.282	−0.265	−0.196	−0.023
	(0.213)	(0.213)	(0.225)	(0.235)
GDP pc	0.529	0.523	0.461	0.418
	(0.286)	(0.287)	(0.286)	(0.286)
IMF Commitment	−0.435			
	(0.224)			
GDP pc × IMF Commitment	0.062*			
	(0.028)			
IMF Disbursement		−0.371		
		(0.247)		
GDP pc× IMF Disbursement		0.053		
		(0.032)		
WB Commitment			−0.358*	
			(0.171)	
GDP pc× WB Commitment			0.050*	
			(0.020)	
WB Disbursement				−0.652***
				(0.185)
GDP pc× WB Disbursement				0.082***
				(0.021)
Lagged Transparancy	0.951***	0.952***	0.949***	0.946***
	(0.007)	(0.007)	(0.007)	(0.007)
Trade	−0.001	−0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	0.069	0.069	0.065	0.056
	(0.052)	(0.052)	(0.052)	(0.052)
UNSC Member	0.014	0.015	0.008	0.006
	(0.034)	(0.034)	(0.034)	(0.034)
Population	0.542	0.535	0.478	0.459
	(0.290)	(0.290)	(0.290)	(0.290)
GDP	−0.523	−0.517	−0.459	−0.436
	(0.287)	(0.288)	(0.287)	(0.287)
Signed BITs	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.042	0.053	−0.002	−0.025
	(0.048)	(0.048)	(0.051)	(0.051)
Asia	0.053	0.055	0.053	0.048
	(0.044)	(0.044)	(0.044)	(0.044)
Europe	0.243***	0.247***	0.235***	0.238***
	(0.050)	(0.050)	(0.050)	(0.050)
Oceania	−0.006	−0.008	0.010	0.011
	(0.057)	(0.057)	(0.057)	(0.057)
Political Instability	−0.006	−0.006	−0.006	−0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Geo-Distance	−0.001	−0.000	−0.004	−0.006
	(0.005)	(0.005)	(0.005)	(0.005)
AIC	1856.169	1859.535	1849.805	1841.984
BIC	1971.435	1974.801	1965.071	1957.250
Log Likelihood	−907.084	−908.767	−903.902	−899.992
Num. obs.	1788	1788	1788	1788
Num. groups: ccode	83	83	83	83
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Table S3: Interactive Term of UNSC and Loan Size

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.509***	−0.497***	−0.535***	−0.550***
	(0.116)	(0.116)	(0.116)	(0.117)
UNCS Member	0.021	0.018	0.037	−0.016
	(0.026)	(0.026)	(0.038)	(0.039)
IMF Commitment	0.003**			
	(0.001)			
UNCS Member × IMF Commitment	−0.000			
	(0.003)			
IMF Disbursement		0.003*		
		(0.001)		
UNCS Member × IMF Disbursement		0.001		
		(0.004)		
WB Commitment			0.004***	
			(0.001)	
UNCS Member × WB Commitment			−0.002	
			(0.003)	
WB Disbursement				0.003***
				(0.001)
GDP pc× WB Disbursement				0.003
				(0.003)
Lagged Transparancy	0.969***	0.969***	0.967***	0.967***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.004	−0.005	−0.003	−0.008
	(0.025)	(0.025)	(0.025)	(0.025)
Population	0.317	0.317	0.257	0.268
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.297	0.297	0.252	0.262
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	−0.289	−0.290	−0.233	−0.244
	(0.188)	(0.188)	(0.189)	(0.188)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.051	0.053*	0.045	0.046
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.046*	0.044*	0.046*	0.048*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.191***	0.189***	0.200***	0.203***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	0.002	−0.000	0.013	0.013
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3418.926	3422.837	3411.417	3414.563
BIC	3549.746	3553.657	3542.236	3545.383
Log Likelihood	−1688.463	−1690.419	−1684.708	−1686.281
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Table S4: Interactive Term of UNSC and Loan Dummy

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.514***	−0.501***	−0.559***	−0.570***
	(0.116)	(0.116)	(0.117)	(0.119)
UNCS Member	0.022	0.019	0.040	−0.020
	(0.026)	(0.026)	(0.038)	(0.039)
IMF Commitment	0.057**			
	(0.019)			
UNCS Member × IMF Commitment	−0.015			
	(0.068)			
IMF Disbursement		0.051*		
		(0.022)		
UNCS Member × IMF Disbursement		0.007		
		(0.081)		
WB Commitment			0.065***	
			(0.016)	
UNCS Member × WB Commitment			−0.040	
			(0.049)	
WB Disbursement				0.057***
				(0.017)
GDP pc× WB Disbursement				0.059
				(0.050)
Lagged Transparancy	0.969***	0.969***	0.967***	0.967***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.004	−0.005	−0.002	−0.007
	(0.025)	(0.025)	(0.025)	(0.025)
Population	0.318	0.319	0.266	0.274
	(0.189)	(0.189)	(0.189)	(0.189)
GDP pc	0.298	0.299	0.259	0.266
	(0.188)	(0.188)	(0.188)	(0.188)
GDP	−0.290	−0.291	−0.241	−0.248
	(0.188)	(0.188)	(0.188)	(0.188)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.052	0.054*	0.046	0.046
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.046*	0.044*	0.046*	0.048*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.191***	0.189***	0.200***	0.203***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	0.002	−0.000	0.012	0.013
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011**	−0.011**	−0.009**	−0.010**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	0.000	0.000	−0.001	−0.000
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3419.727	3423.314	3412.421	3414.544
BIC	3550.547	3554.134	3543.241	3545.364
Log Likelihood	−1688.863	−1690.657	−1685.211	−1686.272
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy_dd_bd_lag	2	2	2	2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Multilevel regression for pooled sample.

Table S5: Simple Linear Model (Loan Size)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.383**	−0.371**	−0.394***	−0.422***
	(0.118)	(0.118)	(0.119)	(0.120)
IMF Commitment	0.004***			
	(0.001)			
IMF Disbursement ln		0.004**		
		(0.001)		
WB Commitment			0.003***	
			(0.001)	
WB Disbursement				0.004***
				(0.001)
Lagged Transparancy	0.978***	0.978***	0.976***	0.976***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.050**	−0.052***	−0.051**	−0.057***
	(0.016)	(0.016)	(0.016)	(0.016)
UNSC Member	0.017	0.018	0.014	0.014
	(0.026)	(0.026)	(0.026)	(0.026)
Population	0.326	0.325	0.267	0.276
	(0.199)	(0.200)	(0.200)	(0.200)
GDP pc	0.310	0.308	0.263	0.274
	(0.198)	(0.198)	(0.199)	(0.199)
GDP	−0.304	−0.303	−0.249	−0.258
	(0.199)	(0.199)	(0.199)	(0.199)
Signed BITs	−0.003***	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.070*	0.073**	0.062*	0.065*
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.058**	0.056**	0.058**	0.060**
	(0.021)	(0.021)	(0.021)	(0.021)
Europe	0.229***	0.227***	0.235***	0.240***
	(0.028)	(0.028)	(0.029)	(0.029)
Oceania	0.006	0.003	0.011	0.015
	(0.043)	(0.043)	(0.043)	(0.043)
Political Instability	−0.010**	−0.010**	−0.009*	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Geo-Distance	0.002	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.971	0.971	0.971	0.971
Adj. R^2	0.971	0.971	0.971	0.971
Num. obs.	3750	3750	3750	3750

Table S6: Simple Linear Model (Loan Dummy)

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.389**	−0.375**	−0.419***	−0.442***
	(0.119)	(0.119)	(0.120)	(0.121)
IMF Commitment	0.064***			
	(0.019)			
IMF Disbursement		0.062**		
		(0.022)		
WB Commitment			0.058***	
			(0.016)	
WB Disbursement				0.062***
				(0.018)
Lagged Transparancy	0.978***	0.978***	0.976***	0.976***
	(0.004)	(0.004)	(0.004)	(0.004)
Trade	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.050**	−0.053***	−0.051**	−0.056***
	(0.016)	(0.016)	(0.016)	(0.016)
UNSC Member	0.017	0.018	0.014	0.015
	(0.026)	(0.026)	(0.026)	(0.026)
Population	0.326	0.327	0.273	0.285
	(0.200)	(0.200)	(0.200)	(0.200)
GDP pc	0.310	0.310	0.268	0.280
	(0.198)	(0.198)	(0.199)	(0.199)
GDP	−0.304	−0.305	−0.253	−0.265
	(0.199)	(0.199)	(0.199)	(0.199)
Signed BITs	−0.003***	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.070**	0.074**	0.063*	0.066*
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.058**	0.056**	0.058**	0.060**
	(0.021)	(0.021)	(0.021)	(0.021)
Europe	0.229***	0.228***	0.235***	0.240***
	(0.028)	(0.028)	(0.029)	(0.029)
Oceania	0.006	0.003	0.011	0.015
	(0.043)	(0.043)	(0.043)	(0.043)
Political Instability	−0.010**	−0.010**	−0.009*	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Geo-Distance	0.002	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.971	0.971	0.971	0.971
Adj. R^2	0.971	0.971	0.971	0.971
Num. obs.	3750	3750	3750	3750

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ Multilevel regression for pooled sample.

Table S7: Loan Per Capita

Covariates	IMF Com.	IMF Disb.	WB Com.	WB Disb.
Constant	−0.502***	−0.490***	−0.529***	−0.547***
	(0.115)	(0.114)	(0.115)	(0.116)
IMF Commitment	0.003**			
	(0.001)			
IMF Disbursement		0.003*		
		(0.001)		
WB Commitment			0.003***	
			(0.001)	
WB Disbursement				0.003***
				(0.001)
Lagged Transparancy	0.968***	0.969***	0.966***	0.966***
	(0.004)	(0.004)	(0.004)	(0.004)
Democracy	0.049**	0.049**	0.044**	0.045**
	(0.017)	(0.017)	(0.017)	(0.017)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Member	−0.005	−0.006	−0.005	−0.009
	(0.025)	(0.025)	(0.025)	(0.025)
UNSC Member	0.019	0.019	0.015	0.016
	(0.024)	(0.024)	(0.024)	(0.024)
GDP pc	−0.022**	−0.022**	−0.008	−0.009
	(0.008)	(0.008)	(0.009)	(0.009)
GDP	0.030***	0.029***	0.026***	0.027***
	(0.006)	(0.006)	(0.006)	(0.006)
Signed BITs	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
America	0.040	0.042	0.033	0.037
	(0.027)	(0.027)	(0.027)	(0.027)
Asia	0.050*	0.048*	0.049*	0.051*
	(0.020)	(0.020)	(0.020)	(0.020)
Europe	0.180***	0.178***	0.190***	0.192***
	(0.028)	(0.028)	(0.028)	(0.028)
Oceania	−0.007	−0.010	0.002	0.004
	(0.041)	(0.041)	(0.041)	(0.041)
Political Instability	−0.011***	−0.011***	−0.010**	−0.011**
	(0.003)	(0.003)	(0.003)	(0.003)
Geo-Distance	−0.000	−0.000	−0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
AIC	3413.390	3417.298	3406.245	3409.961
BIC	3537.980	3541.888	3530.836	3534.552
Log Likelihood	−1686.695	−1688.649	−1683.123	−1684.981
Num. obs.	3750	3750	3750	3750
Num. groups: ccode	125	125	125	125
Num. groups: year	30	30	30	30
Num. groups: democracy	2	2	2	2

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