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# A climate stress-test of the financial system

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# 1 Data acquisition and processing

## 1.1 Company and shareholder data from BvD Orbis

We extracted from the Bureau Van Dijk Orbis database a dataset of $366,225$ equity holdings of $65,059$ global shareholders in $14,878$ EU[1] and US listed companies. Because corporate financial reporting is usually for the previous fiscal year and worldwide data consolidation in Orbis takes some time, all equity holdings refer to the last quarter of 2015. A summary of the data fields downloaded from the relational database is reported in Table 1.

| **Companies** (14,878) | | **Shareholders** (65,059) |
|---|---|---|
| | Name | |
| | BvD ID / LEI / ISIN | |
| | Country ISO code | |
| | NACE Rev2 4-digit code | |
| | Operating revenue | |
| | Total assets | |
| NACE Rev2 one-digit code | | |
| Postcode | | |
| Market capitalization | | |
| Ticker symbol | | |
| | | Shareholder BvD type |
| | | Direct equity holding (%) |
| | | Total equity holding (%) (Direct + indirect) |

**Table 1:** Summary of data fields extracted from the BvD Orbis database. The dataset contains data on $366,225$ equity holdings of $65,059$ global shareholders in $14,878$ EU and US listed companies at the end of 2015. The fields listed have been extracted for each individual company and shareholder. Data fields listed in the middle have been extracted for both shareholders and companies.

### 1.1.1 Missing data

The cumulative value of the equity holdings in our dataset adds up to 93.47% of the total market capitalization of all listed companies in the EU and US. We can therefore effectively map all equity holdings in these companies. Market capitalization data was not

[1] EU 28, UK included

available in the dataset for 3.19% of the listed companies and for 5.23% of equity holdings the fraction of shares owned by the shareholder was not available (both direct and total). Missing data has been neglected in the analysis by removing it from the dataset.

Company data has a good coverage, with only 1.22% of assets data missing and just 8 companies without NACE Rev2 4-digit code (they have been removed from the dataset). Shareholder data has more limited coverage, but limitations concern mostly data fields that do not affect our analysis. Since a majority of shareholders are physical persons (see Table 2) it is expected that certain information is missing in most cases. Data on operating revenue is missing for 82.52% of shareholders, total assets for 83.51%, and NACE Rev2 4-digit codes for 75.46%.

One of the most interesting fields for shareholders is the "Shareholder BvD Type". This data field represents an attempt by Bureau Van Dijk at classifying shareholders into several institutional categories. As it will be explained in Section 2.2, this classification proved inadequate for our purposes. For completeness, Table 2 lists the composition of shareholders in our dataset according to their "Shareholder BvD Type":

| **Shareholder BvD Type** | **Fraction in dataset** |
|---|---|
| Bank | 1.57% |
| Employees/Managers/Directors | 0.82% |
| Financial Company | 7.08% |
| Foundation/Research Institute | 0.64% |
| Hedge Funds | 0.24% |
| Industrial Company | 22.26% |
| Insurance Company | 0.98% |
| Mutual & Pension Fund/Nominee/Trust/Trustee | 12.76% |
| Individuals | 50.10% |
| Private Equity Firms | 1.54% |
| Unnamed Shareholders | 2.01% |

**Table 2:** Breakdown of the $65,059$ global shareholders in the dataset by field "Shareholder BvD Type". Notice the majority of Individuals.

## 1.2 Bank data from BvD Bankscope

In the case of banks we integrated data extracted from the BvD Orbis database with balance sheet data obtained from the Bureau Van Dijk Bankscope database. We focus on the set of the top 50 EU listed banks, by total assets, in 2015. These banks account for 90% of total equity and 95% of total assets of the EU banking sector (counting only listed banks) and are therefore assumed representative of the entire EU banking network. The network structure of bilateral lending contracts among these institutions has been computed through a standard estimation procedure from 2015-Q4 balance sheet data on the total lending and borrowing of each institution. The model employed, the fitness model (Cimini et al., 2014, 2015; De Masi et al., 2009; Musmeci et al., 2013), takes as input the total lending and borrowing of each bank and returns a collection of networks that are consistent with these aggregate data and show a topology (known as core-periphery topology) that is empirically known to correspond to the interbank lending network of various countries. The methodology is identical to the one developed in Battiston et al. (2016) (see Section 4) and consists in:

- simulating a sample of 1,000 networks according to the model (network density 20%),
- running the DebtRank algorithm on each network,
- computing and reporting an empirical network sample measure (e.g. mean) of the global relative vulnerabilities thus calculated.

# 2 Climate-policy-relevant sectors and financial actor types

## 2.1 Climate-policy-relevant sector classification

The classification of sectors is partly inspired by the list provided by the European Commission report 2014/746/EU. We develop a custom classification aimed at identifying climate-policy-relevant sectors. The classification is based on the NACE Rev2 4-digit codes classification adopted in the EU. The complete mapping from NACE Rev2 4-digit codes to our classification is showed in Table 3.

| NACE Rev2 4-digit codes | Sectors |
|---|---|
| B5.1-B6.2, B8.9.2, B9.1, C19.1-C19.2, C20.1.1, C28.9.2, D35.2, F43.1.2, F43.1.3, H49.5 | Fossil-fuel |
| B7.1, B7.2.9, B8.9.1, B8.9.3, B8.9.9, C10.2, C10.6.2, C10.8.1, C19.8.6, C11.0.1, C11.0.2, C11.0.4, C11.0.6, C13.1-C15.2, C16.2.9-C17.1.2, C17.2.4, C20.1.2-C20.2, C20.4.2, C20.5.3-C22.1.9, C23.1.1, C23.1.3-C23.5, C23.7, C23.9.1, C24.1-C24.2, C24.4-C24.4.6, C24.5.1, C24.5.3., C25.4, C25.7, C25.9.4-C28.9.1, C28.9.3-C29.1, C29.3.1, C30.3, C30.9, C31.0.9-C32.9, | Energy-intensive |
| C23.6.1, C23.6.2, C31.0.1-C31.0.3, F41.1, F41.2, F43.1-F43.9, I55.1, L68 | Housing |
| D35.1, F42.2.2 | Utilities |
| H49.1-H49.4, H50-H51.2.1, H52.5-H53.2.0 | Transport |
| K | Finance |
| Other | Other |

**Table 3:** Mapping of sectors from NACE Rev2 4-digit codes to our classification in climate-policy-relevant sectors.

## 2.2 Financial actor type classification

The classification of financial actors has always been traditionally challenging. Many institutional investors offer a broad spectrum of financial services to customers and may be classified simultaneously as asset managers, investment funds, banks (both commercial and investment), pension funds and many more. Generally, most financial companies are organized in subsidiaries offering different financial services and owned by a single holding company, with the result that it is not always clear how to consolidate the different subsidiaries. It is important to allow sufficient detail in classification, in order to identify the function of a single branch, while retaining a general idea of what the ultimate entity, and final receiver of potential financial shocks, is.

Our classification is partly based on NACE Rev2 4-digit codes and partly on the proprietary classification offered by Bureau Van Dijk. NACE codes were not available for 75.46% of shareholders (all the minor ones and of course all Individuals). On the other side the Bureau Van Dijk classification, as offered through the data field “BvD Shareholder Type” does not exactly reflect the traditional taxonomy of institutional investors (for instance, “Blackrock Inc” is considered to be of type “Bank”). For a given shareholder, if the NACE code was provided, we classified it according to Table 4.

| NACE Rev2 4-digit codes | Sectors |
|---|---|
| K64.1 | Banks |
| K64.2, K64.3, K64.9.1, K66.1.2, K66.3 | Investment funds |
| K65.1-K65.3, K66.2 | Insurance and Pension funds |
| K64.9.2, K64.9.9 | Other Credit Institutions |
| K66.1.1, K66.1.9, | Other Financial Services |
| All non-K codes | Industrial Company |

**Table 4:** Partial mapping of shareholders from NACE Rev2 4-digit codes to our classification in financial actors. This classification has been adopted for all shareholders with reported NACE Rev2 4-digit code in our dataset.

For those shareholders for which no NACE 4-digit code was provided, we followed the Bureau Van Dijk classification. This widened our previous classification, forcing us, in particular, to add two new financial actor types:

- Individuals
- Governments

The breakdown by financial actor type for our dataset is shown in Table 5.

| Type | Fraction in dataset | Absolute number in dataset |
|---|---|---|
| Banks | 1.23% | 798 |
| Governments | 0.19% | 125 |
| Individuals | 51.85% | 33,733 |
| Industrial Companies | 22.83% | 14,851 |
| Insurance and Pension Funds | 9.82% | 6,392 |
| Investment Funds | 7.88% | 5,124 |
| Other Credit Institutions | 1.47% | 955 |
| Other Financial Services | 4.74% | 3,081 |

**Table 5:** Relative and absolute number of shareholders in dataset according to our classification of financial actor types.

# 3 Exposures

## 3.1 Relative equity exposures and mean portfolio analysis

Portfolio compositions look similar across all financial actor types. To shed more light on the possible peculiarities of each type of financial actor, it is necessary to analyze relative equity exposures (both in terms of market capitalization of the sectors and total portfolio value of the shareholders). We plotted in Figure 1 the fraction of total market capitalization owned in the Fossil-fuel and Utilities sectors along with the fraction of such equity exposures in the total equity portfolio of each financial actor type. The same is shown in Figure 2, but this time for the sectors of Fossil-fuel, Utilities, and Energy-intensive. The fraction of market capitalization gives information about the size of the equity exposure in climate-policy-relevant sectors for each financial actor type and can also be used to quantify its bargaining power and influence[2] on the underlying companies. The fraction of equity portfolio, on the other hand, quantifies which financial actor types are potentially more exposed to the climate-policy-relevant sectors (see Table 7).

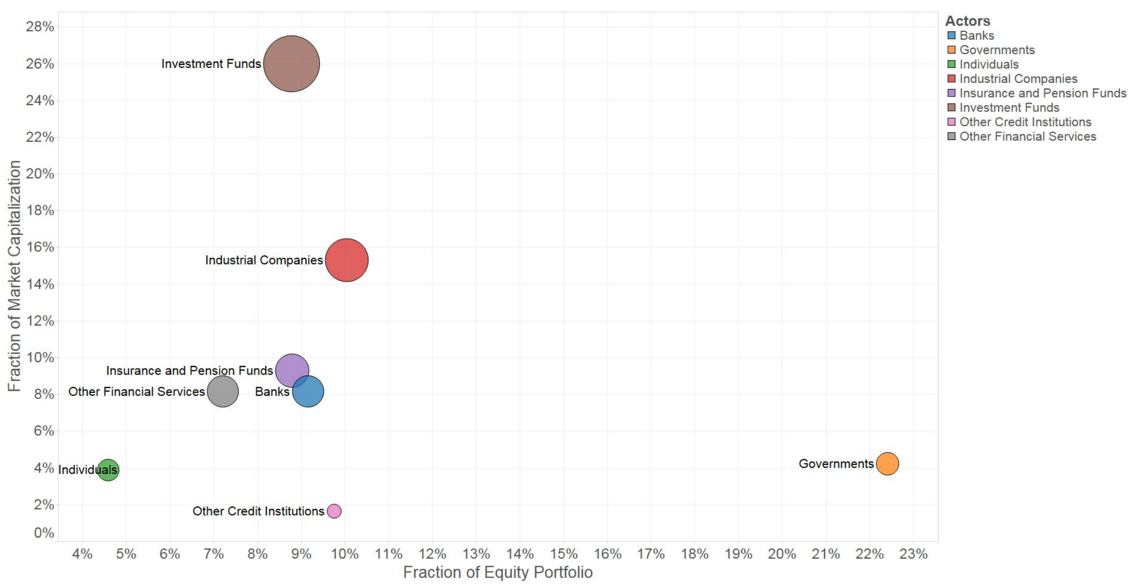


**Figure 1:** Relative equity exposures of financial actor types to Fossil-fuel and Utilities sectors. Bubble size proportional to total equity holdings in EU and US companies.

[2]The term influence is here used, instead of control, to emphasize that most investment funds act as fiduciaries or custodians and are thus seldom interested in exercising voting rights of their shares. Nevertheless, this ownership allows them to potentially exercise direct control on the owned companies. Engagement, next to divestment, is increasingly regarded as a strategy for dealing with carbon risk from an investor perspective.

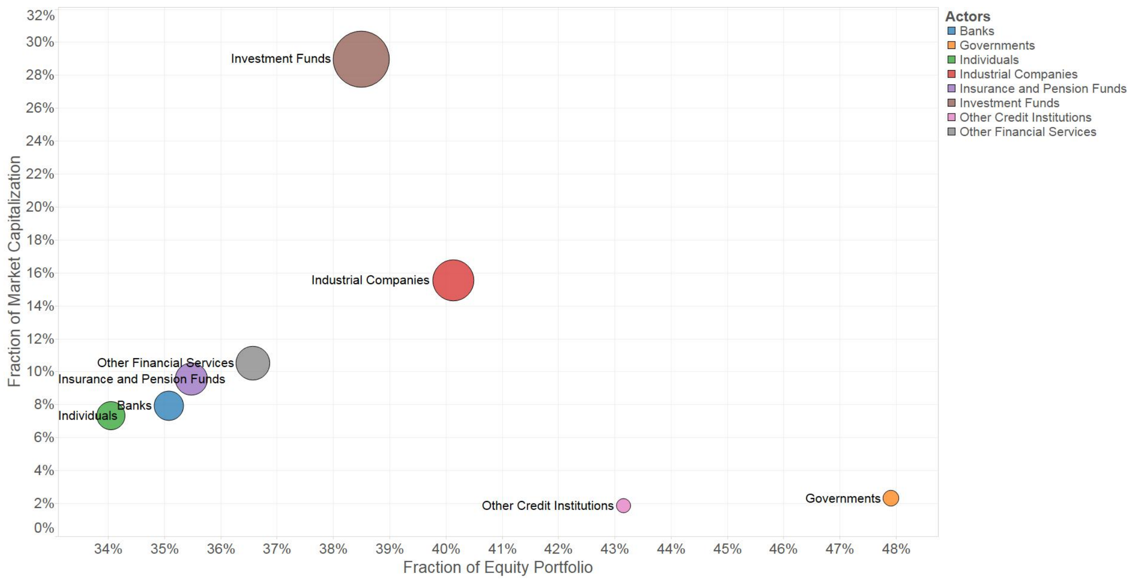


**Figure 2:** Relative equity exposures of financial actor types to Fossil-fuel, Utilities, and Energy-intensive sectors. Bubble size proportional to total equity holdings in EU and US companies.

Investment funds represent the biggest institutional investor by far (in terms of fraction of market capitalization owned), while industrial companies, governments and other credit institutions have the highest relative portfolio exposure. Banks play a minor role, as should be expected by aggregate data and the regulatory burden imposed on them in terms of equity holdings. To further investigate the differences and similarities in portfolio composition among financial actors, we present in Table 6 the mean portfolio for each type of financial actor, together with the standard deviation.

| | IFs (5,124) | Banks (798) | IPFs (6,392) | NFCs (14,851) | OFSs (3,081) | GOV (125) | Individuals (33,733) | OCIs (955) |
|---|---|---|---|---|---|---|---|---|
| Fossil-fuel | 4.91% | 6.87% | 6.16% | 6.12% | 4.73% | 12.88% | 4.38% | 4.08% |
| (767) | 12.43% | 14.05% | 14.26% | 23.13% | 10.28% | 21.68% | 20.40% | 12.14% |
| Utilities | 1.36% | 2.68% | 1.60% | 1.80% | 1.46% | 6.27% | 0.80% | 2.10% |
| (216) | 4.77% | 8.19% | 5.58% | 12.77% | 4.78% | 16.07% | 8.86% | 5.92% |
| Energy-intensive | 27.89% | 24.52% | 25.37% | 27.86% | 25.79% | 19.51% | 27.28% | 21.15% |
| (3956) | 22.06% | 18.91% | 22.05% | 42.89% | 19.31% | 11.35% | 44.44% | 20.95% |
| Housing | 5.03% | 5.84% | 4.68% | 7.52% | 4.06% | 7.69% | 5.21% | 7.13% |
| (797) | 10.85% | 12.38% | 9.99% | 25.59% | 8.98% | 11.46% | 22.17% | 12.92% |
| Transport | 2.46% | 2.59% | 1.93% | 1.90% | 2.13% | 1.32% | 1.19% | 1.53% |
| (224) | 7.51% | 6.15% | 5.68% | 12.95% | 5.83% | 2.06% | 10.82% | 3.23% |
| Finance | 15.09% | 20.09% | 17.98% | 13.03% | 17.89% | 17.01% | 19.86% | 25.77% |
| (2659) | 21.26% | 22.76% | 24.99% | 32.28% | 22.09% | 16.42% | 39.84% | 25.63% |
| Other | 43.27% | 37.43% | 42.29% | 41.75% | 43.93% | 35.32% | 41.27% | 38.25% |
| (6259) | 23.56% | 22.75% | 25.14% | 47.20% | 21.67% | 21.44% | 49.12% | 22.89% |
| Cumulative climate-policy relevant sectors | 41.65% | 42.50% | 39.73% | 45.22% | 38.18% | 47.67% | 38.87% | 35.98% |

**Table 6:** Mean (first row) and standard deviation (second row) of the relative exposure of individual financial actors of given type in each sector as a percentage of the financial actor's total portfolio of equity holdings. The last row represents the cumulative exposure of the average financial actor of each type over all climate-policy-relevant sectors (i.e. Fossil-fuel, Utilities, Energy-intensive, Housing, and Transport).

From Table 6 some specific properties of certain financial actor types emerge. We notice that governments tend to have higher portfolio concentrations than other financial actor types in the Fossil-fuel and Utilities sectors, coherently with the strategic nature of these sectors.

All actors present very big standard deviations, indicating that the underlying sets of portfolios are generally very heterogeneous and a great degree of variability is present, even within a given financial actor type.

In particular individuals and industrial companies show the highest values of standard deviation in every sector, due to the fact that most of these financial actors tend to concentrate their equity holdings in specific companies (as in the case of individuals who own a substantial fraction of shares in the companies they founded) or sectors (as in the case of industrial companies owning several subsidiaries in the same sector as the parent company).

| | OCIs (955) | GOV (125) | Individuals (33,733) | Banks (798) | IPFs (6,392) | OFSs (3,081) | NFCs (14,851) | IFs (5,124) |
|---|---|---|---|---|---|---|---|---|
| Fossil-fuel | 31.17 | 66.17 | 98.17 | 173.29 | 230.21 | 185.15 | 377.30 | 549.85 |
| (767) | 6.02% | 11.43% | 3.77% | 6.34% | 7.09% | 5.33% | 8.06% | 6.05% |
| Utilities | 19.32 | 63.58 | 21.16 | 77.02 | 55.53 | 65.46 | 93.09 | 249.32 |
| (216) | 3.73% | 10.99% | 0.81% | 2.82% | 1.71% | 1.88% | 1.99% | 2.74% |
| Energy-intensive | 172.84 | 147.53 | 766.33 | 708.30 | 865.87 | 1019.84 | 1408.65 | 2701.69 |
| (3956) | 33.40% | 25.49% | 29.47% | 25.92% | 26.68% | 29.36% | 30.08% | 29.71% |
| Housing | 13.26 | 15.88 | 100.57 | 59.07 | 85.28 | 76.60 | 146.72 | 189.36 |
| (797) | 2.56% | 2.74% | 3.87% | 2.16% | 2.63% | 2.21% | 3.13% | 2.08% |
| Transport | 11.43 | 18.48 | 55.38 | 47.67 | 54.48 | 69.96 | 106.67 | 173.02 |
| (224) | 2.21% | 3.19% | 2.13% | 1.74% | 1.68% | 2.01% | 2.28% | 1.90% |
| Finance | 127.01 | 95.33 | 419.63 | 684.72 | 609.11 | 669.82 | 702.44 | 1532.08 |
| (2659) | 24.54% | 16.47% | 16.14% | 25.06% | 18.77% | 19.29% | 15.00% | 16.85% |
| Other | 142.44 | 171.80 | 1139.53 | 982.46 | 1345.08 | 1386.27 | 1847.40 | 3698.41 |
| (6259) | 27.53% | 29.68% | 43.82% | 35.95% | 41.44% | 39.91% | 39.46% | 40.67% |

**Table 7:** Absolute (first row, in USD billions) and relative (second row, percentage of aggregate equity portfolio) exposure of each financial actor type in each sector.

# 4 Stress-test of the financial system

## 4.1 Stress-test methodology

### Framework

We implement a stress-test of the EU banking system using the dataset extracted from BvD bankscope, presented in Section 1.2. The stress-test framework employed is identical to the one presented in Battiston et al. (2016) and allows us to decouple two main contributions to systemic losses:

- *First round losses*, losses in banks' equity due to *direct* exposures to shocked sectors;
- *Second round losses*, *indirect* losses in banks' equity due to the propagation of first round losses on the interbank lending market.

The stress-test is articulated in four main time steps, as outlined in Table 8.

In order to assess systemic losses, we focus on the relative loss in banks' equity, in particular:

| Time | Round | Effects |
|---|---|---|
| $t = 0$ | Initial allocation | Initial allocation of assets and liabilities |
| $t = 1$ | First round | Shock on climate-policy-relevant sectors, losses on banks' balance sheets |
| $t = 2$ | Second round begins | Reverberation of first round losses on the interbank network according to the DebtRank model |
| $t = T$ | Second round ends | Model reaches convergence |

**Table 8:** Outline of stress-test implementation.

1. the *individual vulnerability* of bank $i$

$$h_i(t) = \frac{E_i(0) - E_i(t)}{E_i(0)} \in [0, 1] \tag{1}$$

   defined as the relative cumulative equity loss of bank $i$ up to time $t$,

2. the *global vulnerability* of the system

$$H(t) = \frac{E_{tot}(0) - E_{tot}(t)}{E_{tot}(0)} = \sum_{i=1}^{n} \frac{E_i(0)}{\sum_{j=1}^{n} E_j(0)} h_i(t) \in [0, 1] \tag{2}$$

   defined as the relative cumulative equity loss of the system up to time $t$.

Clearly $h_i(t) = 1$ if bank $i$ has defaulted at any time up to time $t$. Further, we assume that for the entire duration of the stress-test no "injection" of equity or recapitalization is performed, so that $h_i(t)$ is increasing in $t$, i.e. $h_i(t) \geq h_i(t-1)$. In other words we are interested in studying the stability of the financial system in isolation, without positing external interventions of regulators seeking to bail-out institutions or investors willing to invest in banks on the brink of bankruptcy. Notice that this choice of measure for systemic losses allows us to quantify monetarily the impact of shocks on the banking system.

### DebtRank algorithm

The DebtRank model was first developed in Battiston et al. (2012) as a network measure of systemic vulnerability and systemic impact of financial institutions in a network. Unlike other financial contagion models (Eisenberg and Noe, 2001; Furfine, 2003; Rogers and Veraart, 2013) DebtRank assumes that banks implement mark-to-market accounting and CVA practices (Battiston et al., 2016), thus being one of the first financial contagion models to take into account mark-to-market losses (Visentin et al., 2016) as an important channel of contagion, compatibly with empirical evidence from the 2007-08 financial crisis.

The financial contagion process in terms of individual vulnerabilities is the following:

$$h_i(t+1) = \min\left\{1, h_i(t) + \sum_{j \in \mathcal{A}(t)} (1-R) l_{ij}^b h_j(t)\right\},$$

where $l_{ij}^b$ is the interbank leverage of bank $i$ towards bank $j$, $R \in [0,1]$ is an exogenously imposed recovery rate, and $\mathcal{A}(t)$ is the set of active nodes (i.e. those nodes that propagate financial distress onto counterparties at time $t$), defined as:

$$\mathcal{A}(t) = \{j \ \mid \ h_j(t) > 0 \text{ and } h_j(t') = 0, \quad \forall t' < t\}.$$

This definition implies that banks revalue their assets as soon as their counterparties experience financial distress, by losing a fraction of their equity, and even before their counterparties' default (as required by matk-to-market accounting). Nevertheless, once a bank has propagated distress it won't be able to transmit further losses, despite still being able to receive them. This amounts to saying that in this network process only first cycles are considered.

The algorithm is run until convergence[3] and the global vulnerability $H(1)$ quantifies first round losses, while $H(T)$ quantifies second round losses.

### Network ensemble

As already remarked in Section 1.2, data on bilateral financial exposures among banks is not available because of confidentiality agreements. Interbank networks can be reconstructed from the partial information provided by total interbank lending and borrowing of individual institutions. Following standard methodologies (Cimini et al., 2014, 2015; De Masi et al., 2009; Musmeci et al., 2013) we generate a sample of 1,000 interbank networks compatible with total interbank lending and borrowing data and implement the stress-test on each one of the network realizations. The global vulnerability reported in subsequent stress-test results tables will always be the mean global vulnerability over the network sample, simply referred to as "global vulnerability".

If the stress-test is implemented on a shock distribution we run the stress-test for each single realization of the shock on all reconstructed networks and then compute the mean global vulnerability over the network distribution. We can then compute summary statistical measures on this (mean) global vulnerability with respect to the shock distribution

[3] In virtue of the very definition of the set of active nodes, $\mathcal{A}(t)$, the process reaches convergence in finite time.

(thus yielding, for instance, the mean global vulnerability or the VaR). Strictly speaking, therefore, all stress-test results are the result of two averaging processes, the first on the ensemble of reconstructed interbank networks (for which we will always take the mean) and the second on the shock distribution.

## 4.2 Maximum shock scenarios

The results in Table 9 show the impact on the top 50 listed EU banks of a 100% shock in the market capitalization of the climate-policy-relevant sectors identified in Section 2.1 in different, progressive aggregations.

| Sectors shocked (100%) | First Round Relative Equity Loss | Second Round Relative Equity Loss |
|---|---|---|
| Fossil-fuel | 2.55% | (6.08±0.10)% |
| Fossil-fuel<br>+ Utilities | 3.79% | (9.75± 0.15)% |
| Fossil-fuel<br>+ Utilities<br>+ Energy-intensive | 13.18% | (27.91 ± 0.45)% |
| Fossil-fuel<br>+ Utilities<br>+ Energy-intensive<br>+ Housing<br>+ Transport | 15.09% | (30.24 ± 0.40)% |

**Table 9:** First and second round relative losses in banks' equity for the top 50 EU listed banks, under four different 100% shock combinations. Standard deviations on second round losses has been computed on network ensemble distribution.

The results can be interpreted as an absolute upper bound of the potential losses of the EU banks through the contagion channel of equity holdings. A 100% shock on all equity holdings in the respecting climate-policy-relevant sectors allows us to identify an upper bound to the vulnerability of the banking system to the market risk posed by a shock on such sectors, without specifying a necessarily arbitrary shock distribution.

The contributions coming from the second round propagation of direct losses on the interbank lending network (i.e. *indirect* losses) are particularly important, since they quantify in a precise way the amplification of losses due to financial interconnectedness. Typically such amplification is at least as sizable as the first round effect, indicating that failing to take into proper account the interconnectedness of the financial system leads to a severe underestimation of the systemic risk to which the system is exposed.

We further remark that the most significant contribution comes from the Energy-intensive sector, both because of its breadth and because of the substantial equity exposure of banks to it.

In computing first round losses we could not fully take into account banks' subsidiaries. Financial institutions can have a very complex ownership structure and several divisions, each one carrying out financial activities in different institutional sectors, e.g. investment fund, insurance, retail, banking (commercial and/or investment). In particular the equity holding might be recorded as owned by different entities within the same group, for instance UBS AG is a bank while UBS Asset Management is one of its divisions and they both belong to UBS Group AG, which is a holding company. For the moment we have not aggregated the ownership data under the same holding company. Exposures might be relatively higher if this consolidation were taken into account.

## 4.3 Scenarios with shock distribution

**Description of shock distribution from LIMITS project**

We now analyze climate mitigation scenarios via our stress-test methodology using distributions of shocks on climate-policy-relevant sectors computed from the LIMITS Integrated Assessment Model dataset (see Kriegler and al. (2013)). The shock scenarios analyzed in Section 4.2 introduce a 100% shock on equity holdings. These scenarios can be considered as an upper bound on the losses in banks' equity potentially faced by the EU banking industry through equity holdings. Since the results show that exposures are small we conclude that the stability of the financial system would not be affected. It follows that similar results hold if we were to consider scenarios with smaller shocks.

Nevertheless, to study more realistic shock scenarios, we introduce distributions of shocks on the Fossil-fuel and Utilities sector based on the LIMITS database, which provides estimates of the impact of climate mitigation policy on energy sectors according to a set of models, as returns scenarios displaying the stringency and the timing of climate policy.

In particular, we have built a distribution of shocks for three sub-sectors: fossil-fuel, fossil-fuel-based utilities and renewables-based utilities. The LIMITS database provides time series of forecasted production levels for each sub-sector with a five-year interval, up to 2050. We have first normalized these production levels[4] to obtain:

1) the change of market shares of fossil-fuel in the primary energy supply,

[4] The data fields extracted are: "Primary Energy — Fossil" for the Fossil-fuel sector, normalized by "Primary Energy". "Secondary Energy—Electricity—Coal/Gas/Oil" for Fossil-fuel-based Utilities and "Secondary Energy—Electricity—Biomass/Geothermal/Hydro/Non-biomass renewables/Ocean/Solar/Wind" for Renewable-based Utilities, both normalized by "Secondary Energy—Electricity"

2) the change of market shares of fossil-fuel-based utilities in secondary energy supply, and

3) the change of market shares of renewables-based utilities in the secondary energy supply.

From these time series, we can infer a distribution of shocks by assuming that each change in market share from one five-year period to the next one corresponds to an observation of a shock for the corresponding sub-sector.

In so doing, we have obtained one shock per period for each combination of scenario and specific model as specified in the LIMITS dataset, for a total of 5,421 shocks. From an economic viewpoint, interpreting these shocks on market shares as shocks on equity corresponds to making the following simplifying assumptions: (i) the share of nominal expenses on energy is constant (i.e., the demand elasticity of energy substitution is one); (ii) the value of equity in a sub-sector is proportional to its total income; (iii) market valuation is based on one-period (five years) ahead expectations.

Summary statistics for the shocks distributions extracted from the LIMITS database can be found in Table 10 and in the histograms in Figures 3, 4, and 5.

| **Shocks on** | **Mean** | **Median** | **Max** | **Min** |
|---|---|---|---|---|
| Fossil-fuel | -2.40% | -1.75% | +91.23% | -87.96% |
| Utilities Fossil-fuel | -6.24% | -4.90% | +81.22% | -89.17% |
| Utilities Renewable | +10.38% | +8.14% | +88.47% | -39.69% |

**Table 10:** Summary statistics of shocks sample extracted from the LIMITS database. Sample size is 5,421.

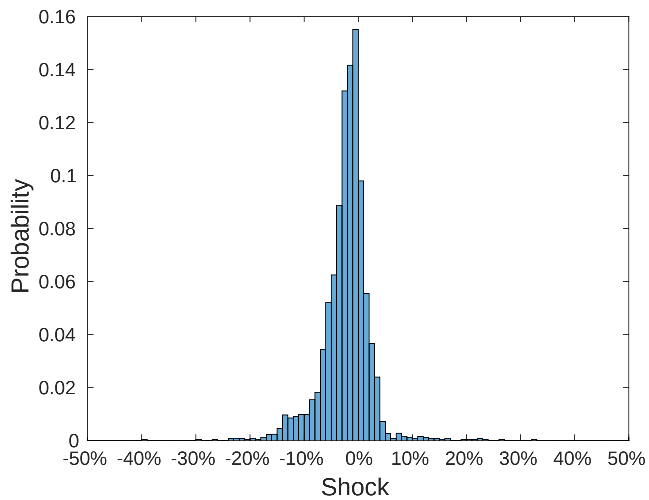


**Figure 3:** Histogram of shock distribution on fossil-fuel sector extracted from the LIMITS database.

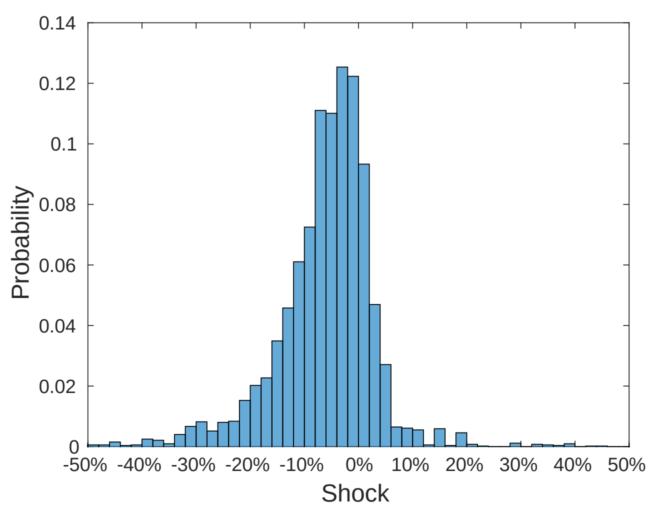


**Figure 4:** Histogram of shock distribution on fossil-fuel-based utilities sector extracted from the LIMITS database.

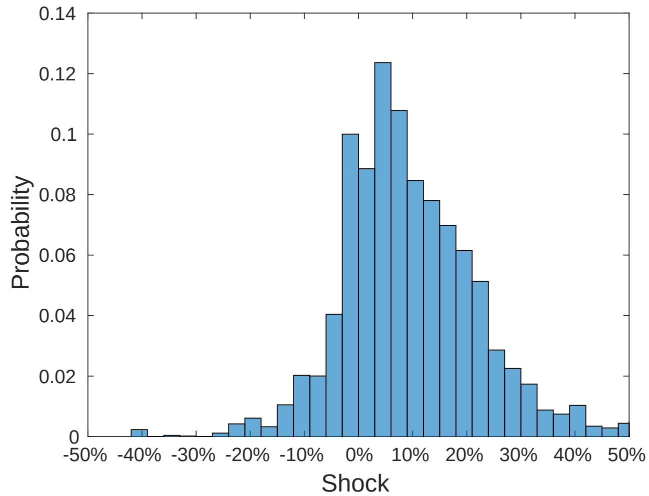


**Figure 5:** Histogram of shock distribution on renewables-based utilities sector extracted from the LIMITS database.

We can see that the fossil-fuel-based utilities sector is mostly negatively impacted by the introduction of mitigation policies, across a variety of scenarios and models. While renewables-based utilities are on average positively impacted. Both samples consists of negative as well as positive shocks.

## 4.4 Stress-test results

We implemented the shocks distributions obtained from the LIMITS database within our stress-test framework. The results, analogous to the ones presented in Section 4, are shown in Table 11.

| Scenario | Round | Mean | Median | VaR(5%) | Max |
|---|---|---|---|---|---|
| Fossil-fuel | 1st<br>1st+2nd | 0.08 %<br>0.18 % | 0.05 %<br>0.11 % | 0.26 %<br>0.63 % | 2.25 %<br>5.34 % |
| Fossil-fuel +<br>Fossil-fuel Utilities<br>**(Brown banks)** | 1st<br>1st+2nd | 0.12 %<br>0.29 % | 0.08 %<br>0.19 % | 0.41 %<br>0.96 % | 2.84 %<br>6.73 % |
| Fossil-fuel +<br>Renewable Utilities | 1st<br>1st+2nd | 0.05 %<br>0.11 % | 0.006 %<br>0.016 % | 0.19 %<br>0.47 % | 2.00 %<br>4.78 % |
| Renewable Utilities<br>**(Green banks)** | 1st<br>1st+2nd | 0.008 %<br>0.019 % | 0.00 %<br>0.00 % | 0.06 %<br>0.13 % | 0.26 %<br>0.62 % |

**Table 11:** Stress-test results for four shock scenarios. Shock distributions obtained from LIMITS project. Statistical measures refer to the global vulnerability of the system (total relative banks' equity loss) at the end of the first and second rounds.

We can interpret the stress-results just shown by studying the variation in assets of the average bank in our dataset. Summary balance sheet quantities and equity portfolio of the average bank are presented in Table 12.

| **Balance sheet quantities** | |
|---|---|
| Equity | USD 32.2B |
| Assets | USD 603.8B |
| Interbank assets | USD 29.1B |
| **Equity holdings** | |
| **Sector** | **Exposure** |
| Fossil-fuel | USD 400M |
| Utilities | USD 214M |
| Energy-intensive | USD 3,025M |
| Housing | USD 397M |
| Transport | USD 4,015M |
| Finance | USD 400M |
| Other | USD 3,022M |

**Table 12:** Basic balance sheet quantities and equity holdings of the average bank in the dataset.

We can illustrate the potential impact on the banking system by considering the distribution of losses in assets for the average bank in case it adopts two representative investment strategies:

- A green bank characterized by all utilities investments in renewables-based utilities and no fossil-fuel investments (scenario 4),
- A brown bank characterized by investments in fossil-fuel and utilities investments in fossil-fuel-based utilities (scenario 2).

Two main results emerge from the first round effect of exposures (see top part of Figure 6): (i) the brown bank incurs more losses than the green one, but (ii) these losses are small in comparison to the total assets of the "average" bank that amounts to 604 bn USD.

Yet, already from the analysis of direct exposures (the first round effect computed here) we can see that the brown bank would be a loser, while the green bank would perform better in terms of losses from climate policy shocks. The results show how climate policies can generate volatility in asset prices and determine winners and losers among financial actors. In particular, the results clearly support the conclusion that climate policies could result in potential winners and losers across financial actors.

Adding to the results of the direct losses the indirect losses due to interbank distress propagation (bottom part of Figure 6), we can see that the addition of the second round effects of losses further polarizes the distribution of losses between the green and brown bank. Indeed, the distribution of losses in assets for the brown bank is mostly negatively affected by the climate policy shock, showing a marked tendency to develop fatter tails, and thus the brown bank clearly emerges as a loser from the stress test.

One can interpret these results as follows. Relative to a baseline of no climate policy, we expect early adapting investors (i.e., those who started to divest from climate-policy-relevant sectors and invest in the green sector) to benefit from positive volatility on assets prices. At the opposite end, investors who continued with the business as usual portfolio allocation on climate-policy-relevant sectors could face losses in assets value. In particular, the results of second round effects show that the "average" brown bank would emerge as a clear loser from climate policy shocks.

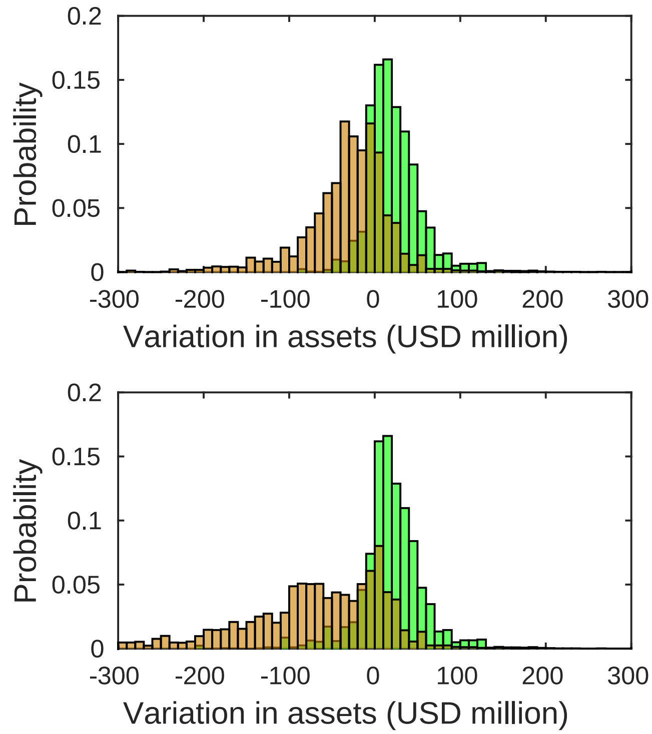


**Figure 6:** Absolute variation in assets for average bank in dataset at the end of the first round (top) and at the end of the second round (bottom) under two investment strategies. Brown bank corresponds to bank with equity holdings in fossil-fuel and fossil-fuel-based utilities. Green bank corresponds to bank with equity holdings only in renewables-based Utilities.

Summary statistics associated to the histograms shown in Figure 6 can be found in Table 13.

| **Round** | **Investment strategy** | **Mean** | **Median** | **Standard deviation** | **VaR(5%)** |
|---|---|---|---|---|---|
| 1st Round | Green bank | +22.25 | +17.46 | 30.50 | 18.07 |
| | Brown bank | -33.10 | -26.55 | 74.65 | 131.27 |
| 1st + 2nd Round | Green bank | +18.47 | +17.45 | 37.66 | 42.53 |
| | Brown bank | -87.04 | -62.67 | 153.62 | 309.92 |

**Table 13:** Summary statistics of asset variations under shock distributions extracted from the LIMITS database for the average brown and green banks. All values are in USD million.

Our methodology is particularly useful insofar as it provides a micro-economic approach to stress-testing. In particular, unlike previous works, we are able to assess and quantify the entity of both direct and indirect losses on individual institutions and investors. In Table 14 we show results analogous to the ones presented in Table 13, but for a specific bank in our dataset, namely BNP Paribas, instead of the average bank in the dataset. We can then see how the choice between the green bank and the brown bank investment strategies would impact BNP Paribas, specifically determining substantially different VaR values.

| **Round** | **Investment strategy** | **Mean** | **Median** | **Standard deviation** | **VaR(5%)** |
|---|---|---|---|---|---|
| 1st Round | Green bank | +96.09 | +75.39 | 131.72 | 78.03 |
| | Brown bank | -182.43 | -144.03 | 430.96 | 730.75 |
| 1st + 2nd Round | Green bank | +89.94 | +79.39 | 143.17 | 121.20 |
| | Brown bank | -276.23 | -207.77 | 563.68 | 1,038.60 |

**Table 14:** Summary statistics of asset variations under shock distributions extracted from the LIMITS database for the individual bank "BNP Paribas", under the two investment strategies corresponding to a brown and a green bank. All values are in USD million.

Given the relevance of VaR as a measure of systemic risk for individual institutions, we present in Figures 7 and 8 the VaR(5%) values at first and second round for the top 20 banks most severely affected, under the green bank and brown bank investment strategies respectively. Notice how the brown bank investment strategy constantly yields VaR values that are typically

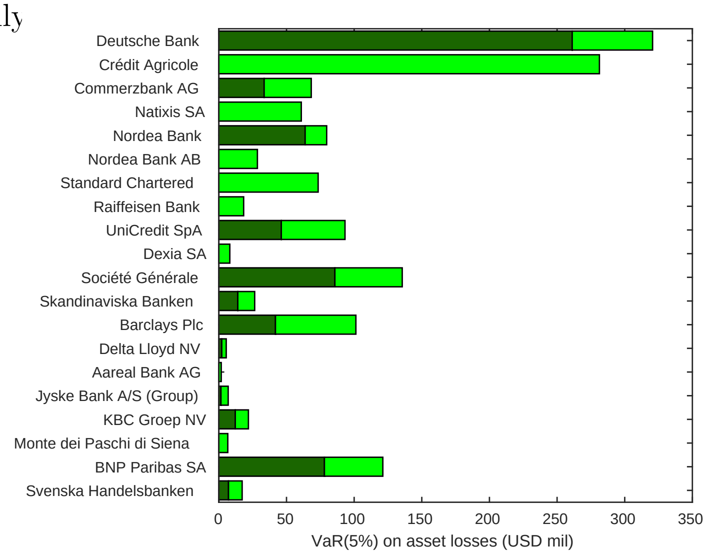


**Figure 7:** Value at Risk at the 5% significance level of the 20 most severly affected EU listed banks in the dataset, under the scenario that they follow the green bank investment strategy. Darker color refers to VaR(5%) computed on the distribution of first round losses only, while lighter color refers to VaR(5%) computed on the sum of first and second round losses

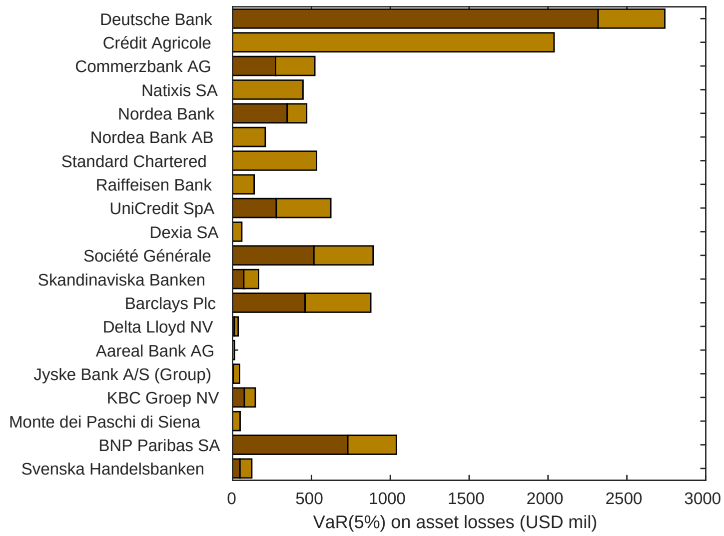


**Figure 8:** Value at Risk at the 5% significance level of the 20 most severely affected EU listed banks in the dataset, under the scenario that they follow the brown bank investment strategy. Darker color refers to VaR(5%) computed on the distribution of first round losses only, while lighter color refers to VaR(5%) computed on the sum of first and second round losses

# 5 Analysis of individual shareholders' portfolios

In Section 3 we saw that mean portfolios show a similar composition across all financial actor types. It is therefore perhaps worthwhile to take full advantage of our dataset, consisting entirely of granular, microeconomic data on individual shareholders, by analyzing and comparing the distributions of portfolios within given financial actor types.

In the analysis of the portfolios of individual shareholders we face a specific limitation of our dataset: it comprises all US and EU listed companies, giving us a good global market capitalization coverage, but it still does not allow us to completely reconstruct the portfolio of each individual shareholder. For instance, 71.55% of shareholders in our dataset have only one recorded exposure, which makes it difficult to reconstruct the portfolio for many individual financial actors. The following table shows a breakdown of numbers of exposures existing in the dataset by financial actor type. For each financial actor type we list in Table 15 the fraction of shareholders of that type for which we have respectively no exposure, only one exposure, two exposures, between two and ten exposures and more than ten exposures in our dataset. The Table summarizes the data presented also in Figure 9 as histograms.

| **Type** | = 0 (%) | = 1 (%) | = 2 (%) | $2 < \ldots \leq 10$ (%) | > 10 (%) |
|---|---|---|---|---|---|
| Banks (828) | 6.64% | 42.75% | 11.96% | 19.20% | 19.44% |
| Governments (125) | 3.20% | 52.80% | 3.20% | 13.60% | 27.20% |
| Individuals (33,733) | 19.46% | 79.27% | 0.82% | 0.35% | 0.01% |
| Industrial companies (14,841) | 15.70% | 69.44% | 5.68% | 5.43% | 3.75% |
| Insurance and pension funds (6,386) | 7.34% | 61.65% | 9.41% | 13.36% | 8.24% |
| Investment funds (5,123) | 11.61% | 53.29% | 8.65% | 13.86% | 12.59% |
| Other credit institutions (955) | 16.13% | 55.92% | 7.75% | 11.52% | 8.69% |
| Other financial services (3,068) | 12.35% | 55.18% | 8.70% | 11.96% | 11.80% |

**Table 15:** Percentage of shareholders of given type with specified number of recorded equity holdings in our dataset. Total number of shareholders of given type reported in parentheses. Each equity holding is intended as recorded equity ownership in a single company.

Table 15 captures some genuine features of the market. For example, it stands to reason that not too many individuals have more than one recorded exposure. Indeed, the vast majority of individuals either have shares in their own company (e.g. Mr. Mark Zuckerberg) or own shares through brokerage or asset management firms, so that a complete portfolio cannot be reconstructed and only a "partial portfolio" could be extracted via Bureau Van Dijk.

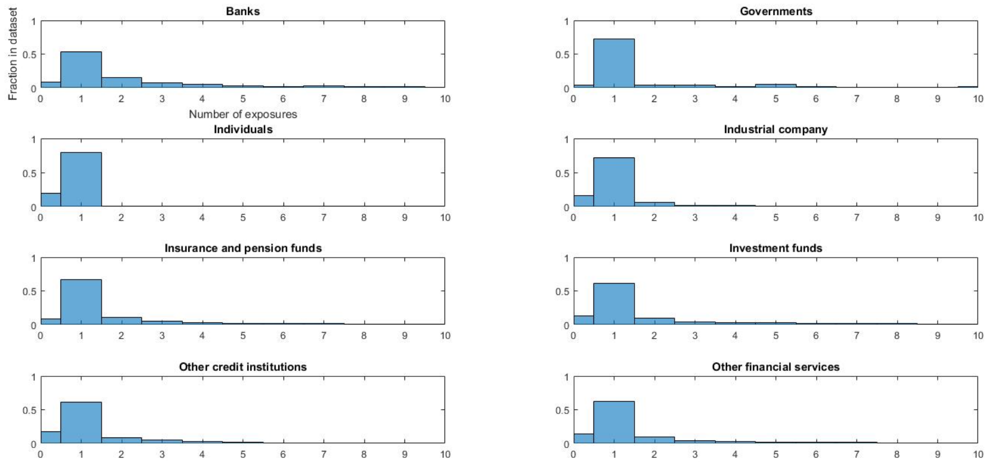


**Figure 9:** Histograms of number of recorded equity holdings in the dataset for shareholders of given type.

For the reconstruction of portfolios, as in Figures 10 and 11 we had to use only those shareholders for which the number of recorded exposures was sufficiently high. In the case of individuals and industrial companies, we selected shareholders with at least two recorded exposures, while for all remaining financial actor types we took only shareholders with more than five recorded exposures. This allowed us to run computations and tests only on those shareholders' portfolios for which we knew with greatest certainty that we had a satisfactorily complete picture. As an example of this methodology we present in Figures 10 and 11 the portfolios of the top 15 banks and 15 investment funds, respectively, in the climate-policy-relevant sectors analyzed.

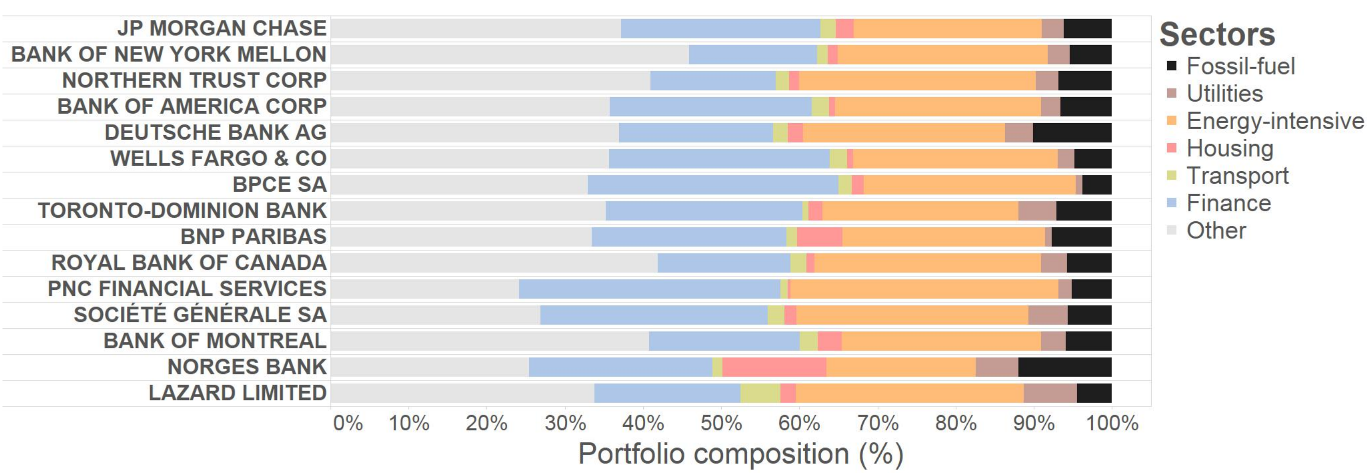


**Figure 10:** Portfolio compositions of the top 15 banks in the dataset.

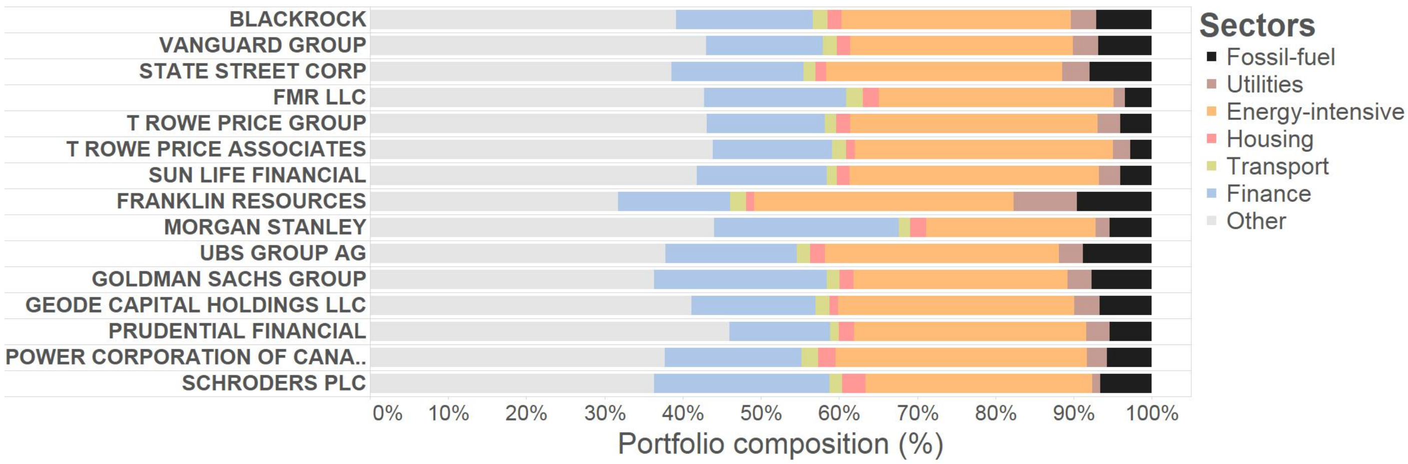


**Figure 11:** Portfolio compositions of the top 15 investment funds in the dataset.

Figures 12 and 13, analogous to Figures 1 and 2, show market share and portfolio share of individual major, global banks in the Fossil-fuel, Utilities, and Energy-intensive sectors.

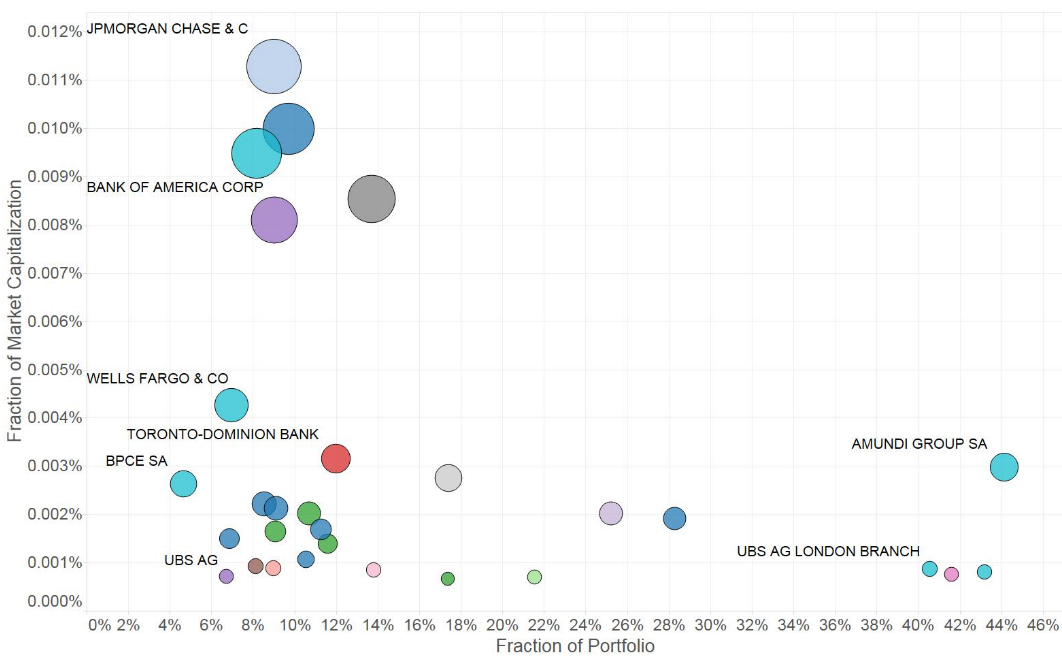


**Figure 12:** Relative equity exposures of major, global banks to Fossil-fuel and Utilities sectors. Bubble size proportional to total equity holdings in EU and US companies.

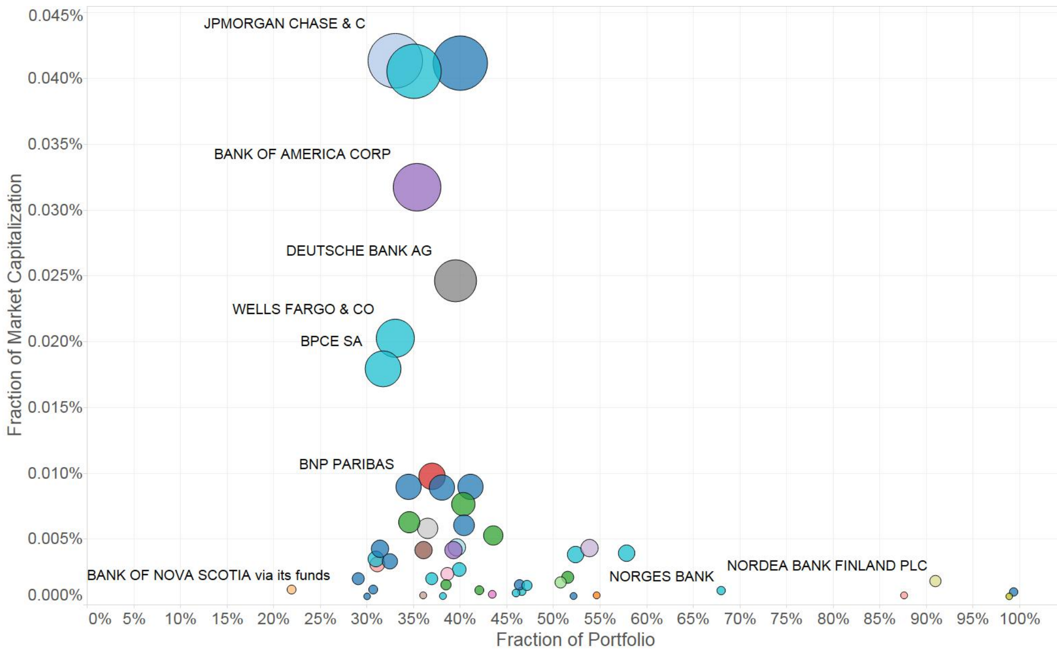


**Figure 13:** Relative equity exposures of major, global banks to Fossil-fuel, Utilities, and Energy-intensive sectors. Bubble size proportional to total equity holdings in EU and US companies.

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