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Abstract

This paper examines whether banks strategically incorporate their competitors' liquidity mismatch policies when determining their own and the impact of these collective decisions on financial stability. Using a novel identification strategy exploiting the presence of partially overlapping peer groups, I show that banks' liquidity transformation activity is driven by that of their peers. These correlated decisions are concentrated on the asset side of riskier banks and are asymmetric, with mimicking occurring only when competitors take more risk. Accordingly, this strategic behavior increases banks' default risk and overall systemic risk, highlighting the importance of regulating liquidity risk from a macroprudential perspective. (JEL G01, G20, G21, G28)

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1 Introduction

Banks have a unique ability to create liquidity by financing illiquid, long-maturity assets such as corporate loans with liquid, short-term liabilities such as demand deposits (Diamond and Dybvig, 1983). This combination of lending and deposit-taking activities protects firms and households against idiosyncratic and systematic liquidity shocks (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006) and promotes economic growth (Bencivenga and Smith, 1991; Berger and Sedunov, 2017). However, due to their fundamental liquidity provision role, banks are also intrinsically fragile. As exposed by the 2007–2009 financial crisis, excessive liquidity mismatch can lead to bank runs, the breakdown of wholesale markets, and distressed asset sales that threaten the solvency of individual banks and the financial system (Brunnermeier, 2009; Tirole, 2011). Nonetheless, as recent theoretical literature emphasizes, the relationship between excessive liquidity transformation and financial instability can be exacerbated even further when banks engage in strategic risk-taking behavior in the form of common portfolio choices (e.g., Farhi and Tirole, 2012; Albuquerque, Cabral, and Guedes, 2019).[1] Using a novel identification strategy exploiting the presence of partially overlapping peer groups, this paper shows empirically that banks do take correlated portfolio decisions and that such strategic behavior has a negative impact on the stability of the financial sector.

The incentive for banks to engage in collective risk-taking strategies can be rationalized on different grounds. Ratnovski (2009), Farhi and Tirole (2012), and Acharya, Mehran, and Thakor (2016), among others, suggest that this behavior occurs due to the presence of bailout guarantees in case of generalized distress. This "too many to fail" problem (Acharya and Yorulmazer, 2007, 2008; Brown and Dinç, 2011) leads to time-inconsistent and imperfectly targeted support to distressed banks to prevent contagion and makes their balance sheet choices strategic complements. Correlated portfolio choices can also be driven by contractual features in the compensation of bank managers. In fact, Albuquerque, Cabral, and Guedes (2019)

[1]While in the subprime mortgage crisis the commonality of asset portfolios at banks was in the form of real estate loans, correlated portfolio choices during booms have been observed in various other forms in many crises throughout history (Reinhart and Rogoff, 2009).

show that relying on relative performance evaluation (RPE) in compensation packages leads managers to disproportionately choose investments that are correlated with with those of their peers. While public guarantees would magnify this mechanism, RPE and associated correlated portfolio choices generate systemic risk even in the absence of a lender of last resort (LOLR).[2] Ultimately, commonality in portfolio exposures and unreasonably high liquidity transformation activity may have a considerably negative impact on financial stability due to higher correlation of defaults, inefficient contagious liquidations, and amplification of the impact of liquidity shocks (Allen, Babus, and Carletti, 2012; Acharya and Naqvi, 2012; Acharya and Thakor, 2016). This can sow the seeds for crises associated with costly recessions and significant distributional consequences (Reinhart and Rogoff, 2009).[3]

While theoretically intuitive, identifying peer effects is empirically challenging since strategic reactions are intrinsically simultaneous (i.e., the reflection problem) and due to potential correlated effects in which all banks in the same local network are subject to unobserved shocks that lead them to choose similar policies (Manski, 1993). To counter these issues, I use an identification strategy based on Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010) in which a structure of connections resembling a social network can be used to solve the reflection problem and construct a valid instrumental variable to account for potential correlated effects. The key feature I exploit is that large cross-border bank holding companies tend to manage liquidity on a global scale and coordinate their risk-management policies within the group (e.g., Cetorelli and Goldberg, 2012a,b; Anginer, Cerutti, and Martinez Peria, 2017). Thus, while not part of the direct peer group of a domestic bank i for liquidity mismatch decision-making, a foreign bank holding group should

[2]Similarly, Ozdenoren and Yuan (2017) predict that when agents have incentives to match industry average efforts, contractual externalities from RPE generate excessive systemic risk-taking. Phelan (2017) and Morrison and Walther (2019) also show that correlated exposures may not necessarily be driven by distorted incentives due to bailout guarantees but as a mechanism to provide ex-post incentives for enforcement and create market discipline. Common portfolio choices may also arise due to learning (i.e., free-riding in information acquisition) that can lead to inefficient outcomes with fully rational agents (Banerjee, 1992). In such case, banks may put more weight on the choices of others than on their own information, particularly when others are perceived as having greater expertise (Bikhchandani, Hirshleifer, and Welch, 1998).

[3]Analyzing 17 advanced economies from 1870 to 2013, Jordà, Richter, Schularick, and Taylor (2017) find that credit growth on the asset side of banks' balance sheet and liquidity mismatch indicators are better predictors of systemic financial crises than solvency measures such as capital ratios.

still indirectly influence the policies of the domestic bank i if such holding company has a subsidiary a that operates in the same country as bank i and that is part of i's local network. This structure of informal decision networks, in line with the theoretical literature on the potential drivers of banks' collective risk-taking strategies, generates "peers of peers" that act as exclusion restrictions to solve the reflection problem. In addition, the policies of such indirect peers can be used as a valid instrument that is orthogonal to the liquidity policies of the domestic banks' peers.

Using a sample of 1,584 commercial banks operating in OECD countries from 1999 to 2014 and the Berger and Bouwman (2009) liquidity creation measure to capture banks' liquidity transformation activity, I first show that financial intermediaries follow the liquidity mismatch policies of their competitors when determining their own. The estimates indicate the economic impact is large and consistent with coordinated behavior where banks constantly adjust to one another's decisions. Specifically, a one-standard-deviation increase in peer banks' average liquidity creation leads to a 5–9 percentage point increase in the liquidity created by individual banks, corresponding to a 16–28% increase relative to the mean. Importantly, these findings are robust to a battery of tests, including numerous peer group definitions, the inclusion of country-year fixed effects to address any remaining omitted variable concerns, an alternative instrument based on market data following Leary and Roberts (2014), as well as the use of the Bai, Krishnamurthy, and Weymuller (2018) Liquidity Mismatch Index (LMI) and the Basel III Net Stable Funding Ratio (BCBS, 2014) as alternative, though complementary, liquidity mismatch indicators.

Given the importance of liquidity created off the balance sheet through loan commitments, standby letters of credit, and other claims to liquid funds (e.g., Kashyap, Rajan, and Stein, 2002), I also consider a more granular quarterly sample of 472 commercial banks operating in the United States during the same period. The estimated coefficients remain economically and statistically significant, as well as remarkably similar in terms of magnitude across the liquidity creation measures with and without off–balance sheet exposures. This confirms the results are robust to the use of higher frequency data and shows that competitors have a negligible impact in the liquidity created by banks off the balance sheet. In fact, when decomposing aggregate liquidity creation into its individual components, I find that the peer effects are concentrated in the asset side of liquidity creation, of which lending is a key element. This result, present in both samples, supports previous evidence pointing toward herding behavior in banks' lending policies (Rajan, 1994; Uchida and Nakagawa, 2007).

In terms of cross-sectional heterogeneity, I show that peer effects in liquidity mismatch decisions are concentrated in ex ante riskier banks with lower profit stability, distance to default, and capital ratios, with the latter suggesting that higher levels of funding liquidity risk are not being compensated with higher capital ratios that could increase a bank's probability of survival during crises (Berger and Bouwman, 2013). I also find that large and small banks' liquidity mismatch decisions are only sensitive to the choices of their respective counterparts—a result indicating that learning (i.e., free-riding in information acquisition) is unlikely to play a major role in this setting. Additionally, such mimicking behavior is relatively stronger among larger banks. This finding is not only consistent with large banks taking more risk than small banks in equilibrium since they internalize that their decisions directly affect the government's optimal bailout policy (Dávila and Walther, 2018), but also with risk-taking being driven by the presence of RPE in compensation schemes that tends to be more prevalent among larger banks (Albuquerque, Cabral, and Guedes, 2019).

Finally, I find that strategic complementarity in liquidity mismatch policies significantly affects the stability of the financial sector. To examine the direction in which these peer effects operate, I first show that the response of individual banks to the choices of competitors is asymmetric. Specifically, individual banks mimic their respective peers only when competitors are increasing funding liquidity risk, thus suggesting that banks' behavior is indeed strategic. I then show explicitly that, consistent with theoretical predictions (e.g., Allen, Babus, and Carletti, 2012), correlated liquidity transformation activities increase both individual banks' default risk and overall systemic risk. Together, these results emphasize the importance of regulating liquidity risk from a macroprudential perspective.

This paper contributes to the literature by empirically showing that banks engage in strategic and correlated portfolio decisions that threaten the stability of the financial sector. Despite extensive research on this issue (e.g., Ratnovski, 2009; Farhi and Tirole, 2012; Vives, 2014; Ozdenoren and Yuan, 2017; Albuquerque, Cabral, and Guedes, 2019), most conclusions are based on theoretical results that lack empirical support. In fact, while there is some evidence of peer effects in banks' lending policies (Uchida and Nakagawa, 2007) and liquidity risk-management decisions (Bonfim and Kim, 2019), these studies are not able to disentangle whether this behavior is driven by banks simply facing common unobserved shocks or sharing common characteristics that lead them to choose similar policies. In addition, this is to the best of my knowledge the first study empirically examining the impact of banks' collective liquidity mismatch decisions on financial sector stability. This issue is particularly relevant after the 2007–2009 global financial crisis, with both academics and policymakers questioning the efficacy of recent liquidity regulatory reforms (e.g., Calomiris, Heider, and Hoerova, 2015; Diamond and Kashyap, 2016; Segura and Suarez, 2017).[4]

While broadly consistent with the literature on bailout guarantees and individual banks' risk-shifting behavior (e.g., Dam and Koetter, 2012), the results also show that moral hazard is not necessarily confined to banks exogenously engaging in excessive risk-taking. Instead, banks can also create aggregate risk by mimicking one another's balance sheet structures and behaving strategically. Besides, unlike Gropp, Hakenes, and Schnabel (2011), the identification framework I use does not restrict collective risk-taking behavior to be driven by distorted incentives due to the presence of the LOLR. Instead, consistent with the theoretical predictions

[4]As distinctly argued by Allen and Gale (2017), "with capital regulation there is a huge literature but little agreement on the optimal level of requirements. With liquidity regulation, we do not even know what to argue about." Ultimately, the Basel III liquidity requirements may play only a limited role in reducing the likelihood of a system-wide liquidity strain, as these requirements target individual banks and abstract from the additional risk of simultaneous liquidity shortfalls due to interconnections between them (IMF, 2011).

of Albuquerque, Cabral, and Guedes (2019), the results suggest that contractual features in bank managers' compensation schemes can also play an important role.[5]

2 Identification Strategy

Empirical Model. Let a given bank i operating in country j at time t be part of a peer group $N_{i,j,t}$ containing a total of $n_{i,j,t}$ peers. Let $y_{i,j,t}$ be the liquidity mismatch position of bank i, and $X_{i,j,t}$ and $Z_{j,t}$ a set of observed bank and country characteristics, respectively. Following the standard linear-in-means model of Manski (1993), bank i's outcome $y_{i,j,t}$ can be expressed as a function of (i) the mean outcome of its peer group $\bar{y}_{-i,j,t}$, (ii) average characteristics of its peer group $\bar{X}_{-i,j,t-1}$, and (iii) bank i's and country j's characteristics:

$$y_{i,j,t} = \mu_i + \beta\bar{y}_{-i,j,t} + \lambda'\bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \delta' Z_{j,t-1} + v_t + \varepsilon_{i,j,t} \tag{1}$$

where,

$$\bar{y}_{-i,j,t} = \frac{\sum_{c\in N_{\mathrm{i,j,t}}} y_{c,j,t}}{n_{i,j,t}}; \bar{X}_{-i,j,t} = \frac{\sum_{c\in N_{\mathrm{i,j,t}}} X_{c,j,t}}{n_{i,j,t}}$$

The coefficient β captures the endogenous effect this paper aims to document—the influence of peers' liquidity mismatch choices on the respective decisions of bank i. Since bank i is excluded, $\bar{y}_{-i,j,t}$ varies not only across countries and over time, but also across banks within each country-year combination. The contextual effects in $\bar{X}_{-i,j,t-1}$ capture the propensity of bank i to change its liquidity transformation policy in response to changes in other characteristics of the peer group such as capital or profitability (e.g., Blume, Brock, Durlauf, and Jayaraman, 2015). Peer-, bank-, and country-level controls are lagged by one period to mitigate concerns of reverse causality. Bank and time fixed effects are represented by μ_i and v_t, respectively.

[5] This paper also complements the recent and growing literature showing that competitors have a significant role on individual firms' decision-making. Empirical evidence on peer effects in corporate actions shows that competitors affect firms' capital structure choices (Leary and Roberts, 2014), stock splits (Kaustia and Rantala, 2015), and dividend payment decisions (Grennan, 2019). Survey evidence also indicates that a significant number of CFOs consider the financing decisions of the competitors important when determining their own (Graham and Harvey, 2001).

Identification Problem. Identifying peer effects is notoriously difficult because of two well-known issues: (i) the reflection problem, a particular case of simultaneity, and (ii) potential correlated or common group effects (Manski, 1993).

First, in standard linear-in-means models in which peer groups are fixed, reflection arises because all agents in a given local network N_{ijt} affect and are affected by all other agents. As a result, one cannot disentangle if bank i's decision is the cause or the effect of its peers' respective choices. This simultaneity in the behavior of interacting agents due to perfectly overlapping peer groups introduces collinearity between the mean outcome of the peer group (endogenous effect) and their mean characteristics (contextual effects). This issue alone prevents the identification of these two effects, even in the absence of unobserved correlated shocks. In contrast, under a structure resembling a social network, peer groups are individual specific and partially overlap. This feature guarantees the existence of "peers of peers"—that is, agents who are not in the peer group of another agent but that are included in the group of one of the peers of this agent. Such indirect peers generate within-group variation in $\bar{y}_{-i,j,t}$ and thus solve the reflection problem (Bramoullé, Djebbari, and Fortin, 2009).

While the presence of a network structure with partially overlapping peer groups allows me to isolate the endogenous effect of interest, it does not necessarily allows me to estimate the causal effect of peers' influence on individual banks' behavior. In fact, the estimation results might still be biased due to the presence of group-specific unobservable factors affecting the behavior of both individual agents and their peers. This can result in banks within the same peer group behaving similarly because they face a common environment or common shocks, rather than as a result of strategic behavior. In other words, even if reflection is perfectly solved, the presence of correlated effects may still impede $\bar{y}_{-i,j,t}$ from being identified.

Identification Strategy. I use a novel identification strategy based on the generalized linear-in-means model of Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010) in which a structure resembling a social network can be exploited to solve the reflection problem and construct a valid IV to account for correlated effects. In detail, the presence of partially overlapping peer groups generates "peers of peers" that can be used as a relevant instrument. By construction, the decision of a certain bank that is not part of bank i's peer group, but is included in the group of one of i's peers, is uncorrelated with bank i's peer group fixed effect and correlated with the mean outcome of i's group through the endogenous interactions (De Giorgi, Pellizzari, and Redaelli, 2010). Such an instrument is therefore orthogonal to the bank i peers' liquidity policies, extracting the exogenous part of its variation and identifying all the relevant parameters.

Importantly, the effect can be identified only if there are banks operating in the same country that have different direct contacts affecting their liquidity mismatch decisions. Such a rich structure of connections is likely to exist in the banking sector since large cross-border banking groups tend to manage liquidity on a global scale (Cetorelli and Goldberg, 2012a,b). As a result, it is reasonable to assume that in addition to the liquidity mismatch choices of its direct competitors, a foreign-owned subsidiary also takes into consideration the overall liquidity transformation policies of its parent bank holding group when determining its own. In such a case, the sets of peers of two given banks do not perfectly coincide if one of them is a foreign-owned subsidiary and the other a domestic bank. This notion is also consistent with Anginer, Cerutti, and Martinez Peria (2017), who find a positive and robust association between parent banks' and foreign subsidiaries' default risk, even when accounting for the default risk of other banks and firms in the home and host countries, as well as global factors. This relationship is partially driven by managers of subsidiaries who are rarely independent from their parents, thus suggesting that their risk-management policies tend to be coordinated.

To illustrate, consider the simple network presented of banks in Figure 1. Bank A, a foreign-owned subsidiary of Bank X, competes in country j at time t with domestic Banks C1, C2, C3, and C4. They interact as follows: (i) Bank A's peer group includes Bank X, its parent bank holding company, and Banks C1, C2, C3, and C4, which operate in the same country and have similar size and business models; (ii) the peer groups of Banks C1, C2, C3, and C4 include only their respective domestic competitors—Bank A and the remaining C banks, but not the foreign parent X. Thus, one can use the liquidity mismatch position of Bank X (the indirect peer) as an instrument for the liquidity choice of the (direct) peers of Banks C1, C2, C3, and C4.[6] This instrument satisfies both the relevance and exclusion restrictions. First, the liquidity mismatch policy of Bank X is relevant for the respective decisions of the peers of Banks C1, C2, C3, and C4 since it should directly influence the liquidity choice of Bank A. Finally, the exclusion restriction is also satisfied if the liquidity decision of Bank X is exogenous to that of Banks C1, C2, C3, and C4's own choice.[7]

Identifying Assumption and Definition of Peer Groups. Following Figure 1, the key identifying assumption is that the foreign parent bank holding group X only affects the decisions of domestic banks C1, C2, C3, and C4 indirectly through the average outcome of peers due to the presence of X's subsidiary. In other words, under such a network structure, a certain domestic bank should have little incentive to directly mimic the liquidity mismatch policies of a bank holding group based in a different country. In this setting, this seems plausible.

First, within-country banks are expected to have higher incentives to mimic their domestic competitors since they share the same LOLR and are more likely to be exposed to the same set of shocks and (correlated) investment opportunities (e.g., Ratnovski, 2009; Farhi and Tirole, 2012). Second, peer influence for learning motives (e.g., Banerjee, 1992) is also more likely to occur within countries since banks share a similar regulatory framework and economic environment, and information for managers of small banks is more accessible. Finally, studies examining the usage of explicit RPE in incentive contracts show that firms select peers

[6] In the case of having only one foreign-owned subsidiary in a peer group, there is no instrument for the liquidity created by subsidiary A's peers, so A must be dropped from the analysis. If there are two or more distinct foreign-owned subsidiaries within the same peer group (e.g., banks A1 and A2 owned by foreign bank holding groups X and Y, respectively), I keep both foreign-owned subsidiaries A1 and A2 in the estimation if the two parents are located in different countries. In such a case, parent Y can identify A1, parent X can identify A2, and for the remaining banks C1–C4, the instrument is the average of parents X and Y's liquidity creation. This is consistent with the framework of Bramoullé, Djebbari, and Fortin (2009) which requires only that some of the indirect peers are not direct peers of the bank in question.

[7] The identifying assumption that a foreign-owned subsidiary considers the liquidity mismatch policy of its parent bank holding company (in addition to that of its domestic peers) should be more appropriate when the subsidiary is not too small or not too large relative to its parent. As a result, I exclude foreign parent bank holding groups when their subsidiaries are more than 50% or less than 1% of the parents' size when computing the IV.

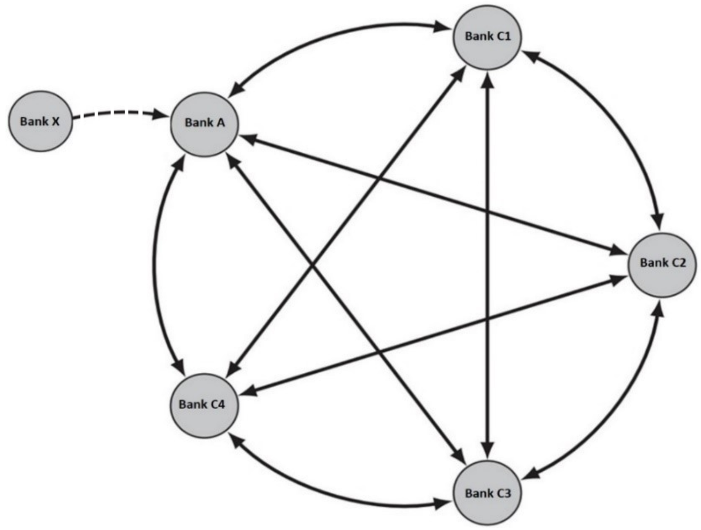

Figure 1
Example of a simple network of banks
The figure shows a network of banks operating in country j in period t under a complete market structure (e.g., Allen and Gale, 2000), but with the presence of a bank holding company based in country p (Bank X) that affects the liquidity mismatch policy of its foreign-owned subsidiary (Bank A). The different institutions interact as follows: (i) Bank A's peer group for liquidity mismatch decision-making purposes includes Bank X (its foreign parent bank holding company) and Bank C1, C2, C3, and C4 (its domestic competitors that have similar size and business model); (ii) the respective peer groups of Bank C1, C2, C3, and C4 include each other and Bank A, but not Bank X—for instance, Bank C1's peer group consists of Bank A, C2, C3, and C4.

narrowly to filter out common exogenous shocks to performance—for instance, based on size, membership in the same local market index, industry, and correlation of stock returns (e.g., Albuquerque, 2009; Bizjak, Kalpathy, Li, and Young, 2018). Given that this evidence may be specific to industries other than the banking sector, Table OA1 in the Online Appendix shows the composition of peer groups for the largest banks operating in the United States in 2016, as reporting of this information in proxy statements is mandatory. The reported peer groups suggest that financial intermediaries indeed choose peers based in the same country for benchmarking purposes.[8]

[8]Citigroup, for instance, in 2016 changed the peer group that is officially used to determine executive pay "due to the increasing challenges associated with comparing executive compensation at US financial services firms to pay at firms headquartered outside the US that are subject to different regulatory environments." This modification of Citi's peer group featured the removal of three foreign banks (Barclays, Deutsche Bank, and HSBC) and inclusion of eight institutions from the United States to create a peer group of thirteen domestic institutions. Consistent with the size criteria I use throughout the paper, the proxy statement also states that "in selecting peers, the Compensation Committee used size-based metrics as primary screening criteria among financial services firms." (Citigroup Inc. Notice of Annual Meeting and Proxy Statement, April 25, 2017).

To incorporate further heterogeneity in peer group composition, I also introduce a size criterion when forming peer groups. In detail, the peer group of a given commercial bank i is defined as other commercial banks of similar size operating in the same country j in the same year t. To ensure that the results are not driven by a particular choice of peer group size, I report results throughout the paper based on size groups of a maximum of 10, 20, and 30 banks—that is, each bank operating in a certain country in a certain year has 9, 19, and 29 competitors, respectively.[9]

Unlike small banks, large banks face both a higher idiosyncratic probability of a bailout during a crisis because they are "too big to fail" and the incentive to herd due to a "too many to fail" effect (Acharya and Yorulmazer, 2007; Brown and Dinç, 2011; Farhi and Tirole, 2012). Both are driven by LOLR bailout guarantees that may lead to excessive risk-taking in the form of excessive liquidity mismatch and correlated risk. Similarly, Dávila and Walther (2018) show that large banks take more risk than small banks in equilibrium since they internalize that their decisions directly affect the government's optimal bailout policy. In addition, free-riding in information acquisition is likely to be driven by a leader-follower model in which small banks' liquidity mismatch choices are affected by the decisions of large banks, but not vice versa. This type of behavior has been shown empirically by Leary and Roberts (2014) for non-financial listed firms in the United States. Finally, the probability of RPE adoption also increases with bank size (Ilic, Pisarov, and Schmidt, 2017; Albuquerque, Cabral, and Guedes, 2019).[10]

[9]The Federal Financial Institutions Examination Council (FFIEC) in the United States also differentiates banks according to asset size and splits them into more than 10 different peer groups. The same set of criteria to define peer groups is also proposed by Berger and Bouwman (2015), who suggest a benchmarking exercise for executives and financial analysts in which a bank would compare its liquidity creation with that of its peers to increase performance. Finally, the choice of peer group size (between 10 and 30 banks) is also consistent with Bizjak, Lemmon, and Nguyen (2011) and Kaustia and Rantala (2015). The former study finds that the average size of the peer group when setting executive compensation is 17.3 for S&P 500 firms and 15.8 for non-S&P firms. The latter computes peer groups based on analyst-following, three-digit SIC codes, and six-digit GICS codes to study peer effects in stock split decisions, and shows that the average peer group size is 11.7, 15.8, and 23.5 firms, respectively, when looking at NYSE-listed entities.

[10]More generally, within-country banks with different size differ significantly in terms of loan portfolio and funding composition. While larger banks tend to use riskier wholesale funding and are more likely to engage in informationally transparent lending, smaller banks rely more on stable deposits and engage in informationally opaque lending to small bank-dependent firms (Song and Thakor, 2007; Berger, Bouwman, and Kim, 2017). Berger and Bouwman (2009) also find that liquidity creation differs significantly across large, medium, and small banks.

3 Sample and Descriptive Statistics

Data. To examine the relationship between banks' strategic liquidity mismatch policies and financial stability, I combine data from several sources and compile (i) a cross-country OECD sample with annual frequency covering banks' financial and ownership information, and (ii) a more granular data set with quarterly bank-level data for the United States.

The main cross-country sample includes 1,584 commercial banks operating in a OECD country from 1999 to 2014.[11] The data on banks' balance sheet and income statements is obtained from BvD/Fitch Bankscope. To have information at the most disaggregated level and avoid double-counting within the same institution, I discard consolidated entries if banks report unconsolidated data.[12] Thus, as in Gropp, Hakenes, and Schnabel (2011), for instance, domestic and foreign subsidiaries are included as separate entities. While most bank-specific variables are expressed in ratios, all variables in levels such as total assets are also adjusted for inflation and converted into millions of dollars.[13] Stock prices and number of shares outstanding are collected from Thomson Reuters Datastream and matched with Bankscope using the International Securities Identification Number (ISIN) for listed banks.

Ownership information for all commercial banks in the OECD sample is manually collected from the BvD ownership database, banks' and national central banks' websites, and newspaper articles obtained from Factiva. The data is further cross-checked with the Claessens and

[11] Out of the 34 OECD members, Estonia, Iceland, Israel, and Sweden are not included in the sample due to the limited number of foreign-owned banks—if any in most years—that would not allow to identify the peer effects of interest.

[12] I go to great lengths to (i) identify duplicate observations in each country-year and thus avoid capturing spurious peer effects, and (ii) check whether the bank specialization reported in Bankscope is accurate. First, in addition to discarding consolidated entries if banks report information at the unconsolidated level, I also look for banks having the same address, nickname, website, or phone and drop the respective duplicates—for instance, banks reporting information with different financial standards in the same year. Second, I cross-check the specialization codes in Bankscope with those reported in Claessens and Van Horen (2015) and adjust them accordingly. Finally, to further ensure that the sample only includes commercial banks—typically defined as institutions that make commercial loans and issue transaction deposits—I exclude banks with deposits not exceeding 5% of liabilities and with loans not exceeding 5% of total assets.

[13] The sample is also restricted to the largest 100 banks in each country, thus excluding smaller (mostly regional) banks in the United States and Japan and limiting the overrepresentation of these two countries. In practice, a bank is excluded if and only if it is not in the top 100 in terms of assets in the country it operates in all years it is active. I also exclude branches of foreign banks since they generally do not report individual information and are not covered by the LOLR of the country they operate.

Van Horen (2015) bank ownership database. Compared with the latter, however, the database I compile is unique in several aspects. First, while the Claessens and Van Horen (2015) database indicates whether a certain bank is foreign-owned and the respective home country of the parent bank, I obtain information on who the actual owner of this foreign-owned bank is and its respective Bankscope identifier.[14] In addition, while Claessens and Van Horen (2015) report the country of ownership based on direct ownership, I obtain information and consider throughout the paper the ultimate bank owner based on a 50% threshold. While limited to OECD countries, the data used in this paper is therefore considerably more detailed and provides a novel source of information.

With respect to country-level variables, I collect information on gross domestic product (GDP) per capita, GDP growth, imports and exports of goods and services, and the Consumer Price Index (CPI) from the World Bank's WDI database and the Federal Reserve Bank (FRB) of St. Louis Economic Data. The date of inception of explicit deposit insurance schemes is obtained from Demirgüç-Kunt, Kane, and Laeven (2015), while the country-level measure of macroprudential regulation intensity (i.e., cumulative sum of changes over time in the usage intensity of capital buffers, interbank exposure limits, concentration limits, loan-to-value (LTV) ratio limits, and reserve requirements) is from Cerutti, Correa, Fiorentino, and Segalla (2017). Banking sector equity market indices are provided by MSCI.

Finally, the quarterly bank-level sample for the United States is from the FFIEC/FRB of Chicago "Call Reports" and includes 472 commercial banks operating from 1999:Q1 to 2014:Q4. These reports containing balance sheet, off–balance sheet, and income statement information are combined with on– and off–balance sheet liquidity creation data available from Christa Bouwman's website. I also obtain stock price data from CRSP and use the CRSP-FRB Link provided by the FRB of New York to match each regulatory bank identifier (RSSD) with a

[14]Consider the United States as an example. While the Claessens and Van Horen (2015) bank ownership database only indicates the home country of the direct owner of HSBC Bank USA (United Kingdom), the database I construct specifies who the ultimate owner is (HSBC Holdings Plc) by providing its Bankscope identifier. With this information and using a parallel Bankscope data set with information at the consolidated level, one can compute the liquidity created by the foreign parent bank holding company and construct the main instrument used in this paper. The ownership data set is publicly available online in my personal website.

unique PERMCO. The sample includes not only individually traded banks but also those that are part of a traded bank holding company. Nonetheless, to ensure that the liquidity is being created by the sample banks, I follow Berger and Bouwman (2009) and exclude banks that are not individually traded and which account for less than 90% of the holding assets.

Liquidity Mismatch Measures. Given that banks hold liquidity on their asset side and provide liquidity through their liabilities, liquidity management is ultimately a joint decision over both assets and liabilities (Gatev, Schuermann, and Strahan, 2009; Cornett, McNutt, Strahan, and Tehranian, 2011; Donaldson, Piacentino, and Thakor, 2018). Thus, I build on the work of Berger and Bouwman (2009) and use their liquidity creation indicator as my main liquidity mismatch measure. By considering the different asset, liability, and equity components of a bank's balance sheet, this structural indicator provides a broad picture of the overall funding mismatch of each financial institution.

In detail, the Berger and Bouwman (2009) liquidity creation (LC) measure for bank i operating in country j at time t is defined as the liquidity-weighted sum of all bank balance sheet items as a share of total assets:

$$LC_{i,j,t} = \frac{\sum_c \lambda_{a_c} A_{i,j,t,c} + \sum_z \lambda_{l_z} L_{i,j,t,z}}{TA_{i,j,t}} \tag{2}$$

where λ_{a_c} and λ_{l_z} are the weights for asset class A_c and liability category L_z, respectively. The liquidity weights are fixed over time and assigned based on the ease, cost, and time it takes for banks to dispose of their obligations to meet a sudden demand for liquidity, and for customers to use liquid funds from banks. Since banks create liquidity by transforming illiquid assets such as corporate loans into liquid liabilities such as demand deposits, both illiquid assets and liquid liabilities are given a positive liquidity weight of $1/2$. Similarly, since banks destroy liquidity when they transform liquid assets such as cash or government securities into illiquid liabilities such as long-term funding or equity, liquid assets, illiquid liabilities, and equity are given a negative liquidity weight of $-1/2$. An intermediate weight of 0 is applied to assets and liabilities that are neither liquid nor illiquid. Since the granularity of the data is different in Bankscope and the Call Reports used in Berger and Bouwman (2009), I adapt their classifications and weights following the authors' criteria as well as the categories defined in their more recent work when using supervisory bank-level data for Germany (Berger, Bouwman, Kick, and Schaeck, 2016)—see Table OA2 in the Online Appendix.

In robustness tests I also consider two distinct, though complementary, liquidity mismatch indicators: (i) the Basel III Net Stable Funding Ratio (NSFR) and (ii) the Bai, Krishnamurthy, and Weymuller (2018) Liquidity Mismatch Index (LMI). The NSFR is a regulatory requirement aimed at encouraging banks to hold more stable and longer-term funding against their less liquid assets, thus reducing liquidity transformation risk. It is defined as the ratio of the available amount of stable funding (ASF) to the required amount of stable funding (RSF) over a one-year horizon. Banks should meet a regulatory minimum of 100%. I use the inverse of the NSFR (denoted NSFRi) so that this indicator is directly comparable to the Berger and Bouwman (2009) liquidity creation measure. While liquidity creation is an indicator of current illiquidity, the NSFR captures what illiquidity would be under a stress scenario (Berger and Bouwman, 2015).[15]

Finally, the Bai, Krishnamurthy, and Weymuller (2018) LMI captures the mismatch between the market liquidity of assets and the funding liquidity of liabilities of a given bank. Unlike the Berger and Bouwman (2009) liquidity creation measure, the liquidity weights are time-varying with market liquidity conditions. In fact, while liquidity mismatch is defined in both measures as the difference of liquidity-weighted assets and liabilities, the LMI uses market measures of market and funding liquidity in addition to bank balance sheet information. These include haircuts from tri-party repo transactions and the secondary loan market to derive the asset liquidity weights, and the three-month OIS–Treasury bill spread used as the funding liquidity factor to compute the liability liquidity weights. While Bai, Krishnamurthy, and Weymuller

[15]The weights to compute the NSFR are also presented in Table OA2 in the Online Appendix. These are given according to the final calibrations provided by the Basel Committee (BCBS, 2014) but also adapted to the granularity of Bankscope data. Where applicable, items are treated relatively conservatively—for instance, all loans are assumed to have a maturity of more than 1 year and hence a RSF weight of 85%.

(2018) use data from the FRY-9C Consolidated Report of Condition and Income containing information on bank holding companies operating in the United States, for consistency with the remainder of the analysis I use Call Reports data instead.[16] I reverse the signs of the LMI and express it as a share of total assets (denoted LMIi) so that, as before, this measure is directly comparable to the Berger and Bouwman (2009) indicator.

Summary Statistics. Table 1 reports descriptive statistics for the main variables in the cross-country sample. The average bank is creating liquidity (0.316), both on the asset (0.169) and liability (0.147) sides of the balance sheet. If in place, it would be complying with the regulatory NSFR (100.3%). Bank-level characteristics include size (ln[total assets]), capital ratio (equity/assets), ROA (net income/assets), deposit share (deposits/assets), NPL provisions (loan loss provisions/assets), liquidity ratio (liquid assets/assets), cost-to-income ratio (non-interest expense/gross revenues), and non-interest income share (non-interest income /total income), all winsorized at the 1st and 99th percentile levels. Country-level characteristics include the logarithm of GDP per capita, GDP growth volatility (standard deviation of GDP growth rate over the past five years), local market concentration (Herfindahl index), the Cerutti, Correa, Fiorentino, and Segalla (2017) prudential regulation intensity measure, global integration (imports plus exports of goods and services to GDP), deposit insurance (a dummy variable equal to 1 if an explicit deposit insurance scheme is in place in country j in year t, and 0 otherwise), and IFRS (a dummy variable equal to 1 if IFRS is in place in country j in year t, and 0 otherwise) to account for potential reporting jumps at the time of a bank's accounting standards change. The bank- and country-level controls are comparable in terms of magnitude to those in previous studies consistently showing their importance for banks' financial decisions (e.g., Beltratti and Stulz, 2012; Beck, De Jonghe, and Schepens, 2013). For completeness, Table OA3 in the Online Appendix presents summary statistics for all the

[16] I first verify that I match the values reported by Bai, Krishnamurthy, and Weymuller (2018) when using FRY-9C. The weights are not affected by business models and, as a result, the LMI can be applied to either bank holding companies or commercial banks. The detailed description of how to construct the LMI is provided in Appendix I of Bai, Krishnamurthy, and Weymuller (2018). The repo haircut data is collected from the SEC Edgar website until 2010 and the FRB of New York since 2010:Q1. The secondary loan market haircuts are from the Loan Syndications & Trading Association. The OIS and Treasury bill data are from Bloomberg.

peer banks' characteristics considered—for instance, peers' average liquidity creation, size, or capitalization. Finally, Table OA4 in the Online Appendix reports summary statistics for the quarterly U.S. sample of 472 listed banks.

Table 1: Summary statistics

Variables	N	Mean	SD	P25	P50	P75
Liquidity mismatch indicators:						
Liquidity creation	13,954	0.316	0.236	0.171	0.342	0.473
Liquidity creation – asset side	13,954	0.169	0.220	0.030	0.225	0.344
Liquidity creation – liability side	13,954	0.147	0.147	0.038	0.145	0.255
NSFRi	13,954	0.997	0.525	0.739	0.892	1.082
Bank-level characteristics:						
Size	13,954	8.319	2.127	6.706	8.166	9.764
Capital ratio	13,954	0.100	0.079	0.056	0.080	0.116
ROA	13,954	0.006	0.013	0.002	0.006	0.011
Deposit share	13,954	0.584	0.221	0.442	0.617	0.760
NPL provisions	13,954	0.004	0.008	0.000	0.002	0.005
Liquidity ratio	13,954	0.078	0.096	0.016	0.039	0.103
Cost-to-income ratio	13,954	0.631	0.285	0.500	0.622	0.744
Non-interest income share	13,954	0.370	0.234	0.203	0.338	0.500
Country-specific characteristics:						
GDP per capita	13,954	10.43	0.552	10.37	10.53	10.71
GDP growth volatility	13,954	0.019	0.012	0.010	0.016	0.025
Concentration	13,954	0.188	0.134	0.097	0.152	0.251
Prudential regulation intensity	13,954	0.562	2.272	-1.000	0.000	1.000
Global integration	13,954	0.832	0.630	0.502	0.615	0.976
Deposit insurance	13,954	0.984	0.124	1.000	1.000	1.000
IFRS	13,954	0.199	0.399	0.000	0.000	0.000

This table presents summary statistics for the variables in the cross-country sample that includes 1,584 commercial banks operating in OECD countries from 1999 to 2014. Liquidity creation is the Berger and Bouwman (2009) on–balance sheet liquidity creation measure divided by total assets. NSFRi is the inverse of the Net Stable Funding Ratio. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing both measures. Bank-level characteristics include size (ln[total assets]), capital ratio (equity/assets), ROA (net income/assets), deposit share (deposits/assets), NPL provisions (loan loss provisions/assets), liquidity ratio (liquid assets/total assets), cost-to-income ratio (non-interest expense/gross revenues), and non-interest income share (non-interest income/total income). Country-level characteristics include the logarithm of GDP per capita, GDP growth volatility (standard deviation of GDP growth rate over the past five years), local market concentration (Herfindahl index), prudential regulation intensity (i.e., cumulative sum of changes over time in the usage intensity of capital buffers, interbank exposure limits, concentration limits, LTV ratio limits, and reserve requirements), global integration (imports plus exports of goods and services to GDP), deposit insurance (a dummy variable equal to 1 if an explicit deposit insurance scheme is in place in country j in year t, and 0 otherwise), and IFRS (a dummy variable equal to 1 if IFRS is in place in country j in year t, and 0 otherwise).

4 Results

4.1 Peer Effects in Banks' Liquidity Mismatch Decisions

Baseline Results. Table 2 reports the benchmark set of results examining whether the liquidity mismatch decisions of a specific bank are determined by the respective choices of its competitors. The table presents 2SLS coefficient estimates of Model (1) using the Berger and Bouwman (2009) liquidity creation measure as the dependent variable and, exploiting the presence of partially overlapping peer groups, the liquidity policy of "peers of peers" as a relevant instrument (Bramoullé, Djebbari, and Fortin, 2009). The row at the top of the table reports the peer effect of interest—that is, the estimated coefficient on the instrumented peer banks' average liquidity creation. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10 (Columns 1–2), 20 (Columns 3–4), and 30 banks (Columns 5–6) according to their size. The regressions in Columns (1), (3), and (5) control for the standard set of bank, peer average, and country characteristics used throughout the paper, while those in Columns (2), (4), and (6) include additional covariates to minimize omitted variable concerns. All specifications include year and bank fixed effects, and the t-statistics in parentheses are robust to heteroskedasticity and within-peer-group dependence.[17]

Consistent with the theoretical predictions of Farhi and Tirole (2012) and Albuquerque, Cabral, and Guedes (2019), among others, the results across all specifications in Table 2 show that the liquidity created by individual banks is significantly and positively affected by the liquidity transformation activity of the respective competitors. To ease the interpretation of magnitudes and ensure comparability across different samples, all coefficients are scaled by

[17] Following the example in Figure 1, the peer group that includes Banks C1–C4 constitutes the relevant cluster to build inference since there is no variation in the instrument across them. In other words, given that the liquidity created by Bank X (the foreign parent bank holding group that owns the foreign subsidiary A) should be positively correlated with that of C1, C2, C3, and C4 through the effect on A's liquidity creation, and since banks C1–C4 become identified using the characteristics of the same Bank X as an instrument, the standard errors should be clustered at the peer group level. While the results are robust to alternative units of clustering, clustering at the peer group level yields considerably more conservative standard errors and first-stage F-statistics—see Table OA5 in the Online Appendix.

the corresponding variable's standard deviation. Thus, a one-standard-deviation increase in peers' average liquidity creation leads to a 5–9 percentage point increase in bank i's liquidity creation, corresponding to a 16–28% increase relative to the mean.[18]

While bank-specific liquidity mismatch decisions are mostly driven by direct responses to the respective policies of competitors, some other peer characteristics such as their average capital and non-interest revenue share also matter for its determination. Nevertheless, their joint effect on individual banks' liquidity decisions is economically small and not robust. This suggests that (i) the results are not likely to be driven by shared characteristics between banks and their respective peers, and that (ii) any bias due to omitted characteristics of competitors that are relevant for bank i's liquidity choices is likely to be small.

Identifying Assumptions. The relevance condition requires the IV to be significantly correlated with peer banks' average liquidity creation (the endogenous variable), and the results in Table 2 show this is indeed the case. In fact, the instrument is always significant at the 1% level in the first stage of the 2SLS estimation in all specifications and the cluster-robust Kleibergen and Paap (2006) F-statistic also rejects the hypothesis of a weak IV.

Together with the relevance condition, the exclusion restriction implies that the only role the instrument plays in influencing the outcome variable is through its effect on the endogenous variable. In other words, the identification strategy solves the endogeneity problem only if the foreign parent bank holding group does not directly influence the liquidity mismatch decision of a domestic bank i. Thus, the estimates may be biased if the liquidity created by the foreign parent is correlated with either an omitted characteristic of peer banks that is relevant for bank i's liquidity policy, or an omitted bank i liquidity creation determinant. While the results discussed above suggest a limited role of the former, the latter concern is addressed as follows.

[18]The unscaled coefficient estimates can be retrieved by dividing each coefficient with the corresponding variable's standard deviation presented in Table OA3 in the Online Appendix. The results in Table OA6 show that this effect is still statistically significant, though underestimated, when using OLS regressions.

Table 2: Peer effects in banks' liquidity mismatch decisions

Liquidity creation	(1)	(2)	(3)	(4)	(5)	(6)
Peers' liquidity creation	0.055***	0.050**	0.069***	0.062***	0.088***	0.081***
	(2.905)	(2.478)	(4.370)	(3.648)	(4.946)	(4.031)
Peers' size	0.010	0.010	0.009	0.009	0.007	0.007
	(1.193)	(1.255)	(1.132)	(1.196)	(0.705)	(0.755)
Peers' capital ratio	0.004	0.003	0.013**	0.011*	0.019***	0.016**
	(0.744)	(0.598)	(2.137)	(1.821)	(2.694)	(2.631)
Peers' ROA	0.002	-0.001	-0.003	-0.005	0.003	0.004
	(0.914)	(-0.210)	(-0.897)	(-1.419)	(0.734)	(0.926)
Peers' deposit share	0.003	0.003	-0.001	0.001	0.004	0.005
	(0.694)	(0.836)	(-0.199)	(0.113)	(0.765)	(0.916)
Peers' NPL provisions	0.002	0.001	-0.001	-0.002	0.002	0.003
	(0.969)	(0.293)	(-0.495)	(-0.655)	(0.656)	(0.897)
Peers' liquidity ratio		0.007		0.006		0.009*
		(1.596)		(1.058)		(1.678)
Peers' cost-to-income		-0.005		-0.003		0.001
		(-1.427)		(-0.883)		(0.200)
Peers' non-interest income share		0.008***		0.010***		0.011***
		(2.661)		(2.944)		(3.055)
Peer group size	10	10	20	20	30	30
No. observations	10,575	10,575	13,023	13,023	13,954	13,954
No. banks	1,407	1,407	1,528	1,528	1,584	1,584
No. peer groups	141	141	80	80	59	59
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	21.67***	19.23***	15.44***	14.97***	12.12***	10.14***
First-stage instrument	0.016***	0.015***	0.019***	0.017***	0.017***	0.015***
	(4.656)	(4.385)	(3.929)	(3.870)	(3.481)	(3.184)
Mean of dependent variable	0.304	0.304	0.313	0.313	0.316	0.316

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bouwman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

First, Columns (1) to (3) of Table 3 report the results of an extended version of Model (1) with country×year fixed effects for country-year pairs with more than one peer group. Despite being slightly smaller in magnitude, the estimated coefficients are still economically and statistically significant, with estimates ranging from a 4 to 7 percentage point increase in bank i's liquidity creation following a one-standard-deviation increase in the liquidity created by its competitors. This result corroborates the previous findings and helps ruling out alternative explanations such as the effect being driven by changes in regulations or supervisory effort that the model may not able to perfectly control for.

Second, to mitigate any remaining concerns that the results may still be biased due to omitted time-varying bank characteristics, I apply the methodology developed by Altonji, Elder, and Taber (2005) to quantify the relative importance of any remaining omitted variable bias. Coefficient stability is computed as the ratio between each coefficient estimate including controls as reported in Table 2 (numerator), and the difference between the latter and the coefficient derived from a regression with the same number of observations but without any controls (denominator). The results suggest that to explain the full effect of peers' liquidity creation, the covariance between unobserved factors and peers' liquidity creation would have to be between 10.09 to 58.58 times as high as the covariance of the included controls. In comparison, Altonji, Elder, and Taber (2005) estimate a ratio of 3.55, which they interpret as evidence that unobservables are unlikely to explain the effect they analyze. Accordingly, one can conclude that the likelihood that unobserved heterogeneity explains the documented peer effects is likely to be small.

Finally, the identifying assumption may still not be satisfied if the country where the foreign parent bank holding company is headquartered and the country where the domestic banks operate were subject to similar shocks that could influence the liquidity they both create. To address this concern, I repeat the analysis with a modified IV that purges the common variation in the baseline instrument. In detail, I first regress the liquidity created by the foreign parent with observed country-level characteristics as well as country and time fixed effects. Then, the estimated residual $\hat{\varepsilon}_{p,j,t} = \widehat{LC}_{p,j,t} - \hat{\tau}' Z_{j,t-1} - \widehat{\omega_j} - \widehat{\upsilon}_t$ is used as an instrument for peer banks' liquidity mismatch choices. This residual should better capture the idiosyncratic nature of the foreign parents' liquidity transformation risk management policies and thus offers a useful test for identifying exogenous variation. The coefficient estimates reported in Columns (4) to (6) of Table 3 remain statistically and economically significant.

Robustness Tests. I conduct a battery of tests to ensure the previous findings are robust. First, to confirm that the results are not being driven by the choice of instrument used to identify peer banks' liquidity creation choices, Columns (1) to (3) of Table 4 show that the previous estimates are robust to the use of an alternative IV based on market data. In detail, following the identification strategy in Leary and Roberts (2014), the liquidity mismatch decisions of competitors are now instrumented with the lagged idiosyncratic component of peer banks' equity returns. Specifically, I extract the idiosyncratic variation in stock returns using a traditional asset pricing model augmented by a factor to purge common variation among peers. The residual from this model is then lagged by one year and used to extract the exogenous variation in peer banks' liquidity choices—see a detailed description of the methodology in Online Appendix A. Compared with the main identification strategy used in this paper, however, this instrument only allows to identify the subset of publicly listed banks in the sample. Nevertheless, the main results remain unchanged.

Second, given that in the benchmark case each bank i in country j in year t belongs to a certain peer group of up to 30 banks based on their size, banks 30 and 31 in a size rank, for instance, would never interact with each other as they belong to different peer groups. Besides, bank 30 would give equal weight to the liquidity profile of banks 1, 2,. . . , 29, even if there is a substantial difference in terms of size between banks 1 and 29. To ensure this modeling choice is not driving the results, I also construct peer-weighted averages based on the size similarity (inverse of the Euclidean distance) between all banks operating in country j in year t, such that the smaller the distance between two banks in terms of size, the more weight the relationship has. Specifically, the peer influence weight between bank i and p operating in the same country in the same year is defined as:

$$Weight_{SizeSimilarity_{i-p,j,t}} = \frac{\max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|}{\sum_{p=1}^{N} \max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|} \tag{3}$$

where $\max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|$ is the inverse of the Euclidean distance between the size of bank i and p in country j in year t, and $\sum_{p=1}^{N} \max(TA_{j,t}) - |TA_{i,j,t} - TA_{p,j,t}|$ is the sum of all the inverse size distances in country j in year t. By construction, the sum of weights in each country in each year is equal to 1. The estimate presented in Column (4) of Table 4 is not only statistically significant, but also in line in terms of magnitude with the coefficients reported in Table 2.

Third, Columns (5) to (7) of Table 4 present the results of a falsification test where the analysis is conducted under the assumption that individual commercial banks follow other financial institutions of similar size and business model but irrespective to the country where they operate. This test is particularly important to ensure the peer groups are defined correctly. In practice, I first rank all banks operating in OECD countries according to their total assets, group them into peer groups of 10, 20, or 30 banks, and then construct the peer averages for each bank accordingly while excluding bank i. The reported estimates show no statistically significant results for the coefficient of interest, no matter how peer groups are defined. In other words, individual banks' liquidity mismatch policies are not sensitive to those of banks of similar size that operate abroad. This is consistent with the a priori assumption when forming peer groups that within-country banks are expected to have higher incentives to mimic their competitors.

Fourth, to further ensure that the results are not driven by a particular choice of peer group, I show in Panel A of Table OA7 in the Online Appendix that the conclusions remain the same when considering alternative peer size groups of 5, 15, or 50 banks—that is, each bank operating in a certain country in a given year has a maximum of 4, 14, and 49 competitors, respectively.

Fifth, while the identifying assumption that a foreign-owned subsidiary considers the liquidity mismatch policy of its parent bank holding group (in addition to that of its domestic peers) should in principle be more appropriate when the subsidiary is not too small or not too large relative to its parent, the results reported in Panel B of Table OA7 in the Online Appendix show that the conclusions remain the same if not restricting the size of the parents in relation to their respective subsidiaries when computing the IV. Similarly, the results are also robust to more stringent relative size restrictions. These include excluding foreign parent bank holding groups in which their respective subsidiaries are more than 25% or less than 1% of the parents' size (when tightening the "too big" restriction in relation to the baseline case), and excluding foreign parent bank holding groups in which their respective subsidiaries are more than 50% or less than 10% of the parents' size (when tightening the "too small" restriction in relation to the baseline case).

Sixth, the conclusions do not change when considering the inverse of the NSFR (NSFRi) as an alternative, though complementary, liquidity mismatch indicator—while liquidity creation is an indicator of current illiquidity, the NSFR captures what illiquidity would be under a stress scenario (Berger and Bouwman, 2015). Panel A of Table OA8 in the Online Appendix follows the same structure of Table 2, and the reported 2SLS estimated coefficients corroborate the previous findings: the first-stage regression coefficient estimates and the Kleibergen and Paap (2006) F-statistic show that the instrument is relevant and not weak, and the estimates on the coefficient of interest indicate that the relationship between the liquidity transformation risk of individual banks and those of its peers is positive and statistically significant in all specifications.

Finally, the main findings also remain unchanged (i) when excluding banks operating in the United States, thus suggesting that such collective behavior is pervasive across OECD countries, (ii) when excluding all foreign-owned subsidiaries from the estimations, (iii) when using the lagged peer banks' liquidity creation (instead of a contemporaneous measure) as the main explanatory variable, (iv) without winsorizing any of the control variables, and (v) when removing from the sample banks with asset growth above 75% in any of the years they are active, since these may have been involved in mergers and acquisitions—see Tables OA8 and OA9 in the Online Appendix.

Table 3: Peer effects in banks' liquidity mismatch decisions – additional tests

Liquidity creation	Country-year fixed effects			Modified instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' liquidity creation	0.040**	0.044**	0.074*	0.076***	0.089***	0.103***
	(2.037)	(2.424)	(1.754)	(3.030)	(6.195)	(5.732)
Peer group size	10	20	30	10	20	30
No. observations	10,228	10,822	9,964	9,298	12,337	13,563
No. banks	1,375	1,315	1,163	1,362	1,509	1,569
No. peer groups	137	68	41	140	79	58
Bank characteristics	Y	Y	Y	Y	Y	Y
Peers avg. characteristics	Y	Y	Y	Y	Y	Y
Country controls	-	-	-	Y	Y	Y
Year FE	-	-	-	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Country-year FE	Y	Y	Y	N	N	N
First-stage KP F-stat	12.80***	10.17***	9.62***	13.82***	12.79***	10.76***
First-stage instrument	0.013***	0.016***	0.008***	0.011***	0.013***	0.013***
	(3.578)	(3.189)	(3.102)	(3.717)	(3.576)	(3.280)
Mean of dependent variable	0.300	0.305	0.313	0.302	0.313	0.315

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bouwman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 4: Peer effects in banks' liquidity mismatch decisions – robustness tests

Liquidity creation	Alternative instrument			Weighted peer avg.	Peer groups defined globally		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peers' liquidity creation	0.095***	0.086***	0.087***	0.091***	0.012	0.013	0.037
	(2.881)	(3.105)	(3.108)	(4.442)	(0.888)	(0.632)	(1.206)
Peer group size	10	20	30	-	10	20	30
No. observations	2,983	2,983	2,983	15,418	11,836	14,502	15,179
No. banks	287	287	287	1,674	1,407	1,528	1,584
No. peer groups	34	23	20	-	126	64	43
Bank characteristics	Y	Y	Y	Y	Y	Y	Y
Peers avg. characteristics	Y	Y	Y	Y	Y	Y	Y
Country controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y
First-stage F-stat	16.19***	24.31***	22.83***	116.8***	17.84***	5.89**	1.70
First-stage instrument	0.007***	0.008***	0.008***	0.015***	0.008***	0.005**	0.003
	(4.023)	(4.930)	(4.778)	(10.808)	(4.224)	(2.428)	(1.303)
Mean of dependent variable	0.389	0.389	0.389	0.318	0.321	0.322	0.322

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bowwman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within bank dependence in Columns (1)–(4), and to heteroskedasticity and within-peer-group dependence in Columns (5)–(7). Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

U.S. Evidence. As a final robustness test, I reiterate the previous analysis when considering a quarterly sample of banks operating in the United States. Restricting the analysis to this panel of banks serves multiple purposes. First, using data from the Call Reports ensures that the results are not driven by potential problems in Bankscope in terms of different definitions of certain balance sheet categories across countries. Second, it preserves homogeneity in terms of regulatory framework, accounting standards, and economic conditions. Third, it allows testing whether the results on peer influence are sensitive to the use of higher frequency data. Finally, since the information provided is considerably more granular, it also allows using the Berger and Bouwman (2009) on– and off–balance sheet liquidity creation measure as the dependent variable. The latter is particularly relevant given the extensive literature highlighting the importance of off–balance sheet liquidity creation through loan commitments, standby letters of credit, and other claims to liquid funds (e.g., Kashyap, Rajan, and Stein, 2002). In the United States, for instance, this accounts for almost half of all liquidity created (Berger and Bouwman, 2009).

In detail, Table 5 reports two-stage least squares estimates of Model (1) using both the Berger and Bouwman (2009) on– and off–balance sheet (Columns 1–3) and on–balance sheet (Columns 4–6) liquidity creation measures divided by total assets as the dependent variables. Since there are no corresponding quarterly level data for most parents of foreign subsidiaries operating in the United States, it is not possible to use here this paper's main identification strategy based on Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010). Besides, there are only a few small, mostly regional, foreign-owned subsidiaries operating in the United States, which would not allow to identify a large portion of the domestic banks in the sample. To counter this issue, I follow Leary and Roberts (2014) and, as in Columns (1)–(3) of Table 4, use as IV the lagged peer bank average equity return shock. In this case, standard errors are clustered at the bank level since the instrument varies across banks and over time. The estimated coefficients are still significant as well as similar in terms of magnitude across the liquidity creation measures with and without off–balance sheet exposures.

This suggests that peer banks have a negligible impact in the liquidity created by individual banks off the balance sheet. I explore this hypothesis in detail in the next section.

Finally, Table 6 considers the Bai, Krishnamurthy, and Weymuller (2018) Liquidity Mismatch Index (LMI) as the outcome variable. Despite relatively fewer observations when compared with Table 5 due to the more granular nature of the data required to compute this measure and since some of the market data is only available from 2002:Q2, the LMI has the advantage of using liquidity weights that are time-varying with market liquidity conditions. The baseline results still hold when considering this measure capturing the mismatch between the market liquidity of assets and the funding liquidity of liabilities of a given bank—both its on– and off–balance sheet (Columns 1–3) and on–balance sheet (Columns 4–6) versions.

4.2 Mechanisms and Heterogeneity

Asset versus Liability Side of Liquidity Creation. The results so far show that competitors play a significant role in determining variations in liquidity mismatch policies of individual banks. Nonetheless, peer influence can be concentrated or at least affect in a dissimilar way liquidity created on the asset and liquidity sides of banks' balance sheets. Berger, Bouwman, Kick, and Schaeck (2016), for instance, show that capital support measures reduce banks' asset-side liquidity creation while increasing by a similar magnitude the liquidity created on the liability side. To better examine the mechanisms through which these adjustments operate, I decompose aggregate liquidity creation into its individual elements (i.e., asset side, liability side, and off–balance sheet liquidity creation—each divided by bank assets), and regress them on peer banks' corresponding component of liquidity creation.

The results reported in Tables 7 and OA10 indicate that peer effects are concentrated on liquidity created on the asset side of banks' balance sheets. Specifically, Table 7 considers the cross-country OECD sample with annual frequency where the instrument is defined as the foreign subsidiary's parent asset or liability-side liquidity creation within each peer group. As in Table 2, standard errors are robust to heteroskedasticity and within-peer-group dependence.

Table 5: Peer effects in banks' liquidity mismatch decisions – U.S. sample

	Liquidity creation (on– and off–B/S)			Liquidity creation (on–B/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' liquidity creation (on– and off–B/S)	0.085**	0.050**	0.040***			
	(2.399)	(2.220)	(2.955)			
Peers' liquidity creation (on–B/S)				0.061***	0.039***	0.027***
				(2.754)	(2.727)	(3.130)
Peer group size	10	20	30	10	20	30
No. observations	14,407	14,407	14,407	14,407	14,407	14,407
No. banks	472	472	472	472	472	472
Bank characteristics	Y	Y	Y	Y	Y	Y
Peers avg. controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	12.88***	24.22***	110.2***	18.10***	36.66***	155.3***
First-stage instrument	-0.002***	-0.003***	-0.005***	-0.002***	-0.003***	-0.004***
	(-3.588)	(-4.922)	(-10.498)	(-4.255)	(-6.055)	(-12.460)
Mean of dependent variable	0.474	0.474	0.474	0.367	0.367	0.367

The table reports two-stage least squares (2SLS) estimates of Model (1) using the quarterly U.S. sample of listed banks and the Berger and Bouwman (2009) on– and off–balance sheet and on–balance sheet liquidity creation measures divided by total assets as the dependent variables. The summary statistics are presented in Table OA4 in the Online Appendix. The instrument is the Leary and Roberts (2014) lagged peer bank average equity return shock. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the United States in the same quarter grouped into a maximum of 10, 20, or 30 banks according to their size. Bank-specific characteristics include size, capital ratio, ROA, deposit share, and NPL provisions. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one quarter. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Instead, Table OA10 in the Online Appendix focuses on the U.S. sample with quarterly frequency as in Table 5, where the instrument is the lagged peer bank average equity return shock and the standard errors are clustered at the bank level. The reported estimates show no statistically significant results for liability-side liquidity creation, a finding that is robust irrespective of the sample, identification strategy, and peer group definition used. Table OA11 in the Online Appendix presents the results with total liquidity creation further decomposed into its off–balance sheet component when using the quarterly U.S. sample. As with liability-side

Table 6: Peer effects in banks' liquidity mismatch decisions – LMI

	LMIi (on– and off–B/S)			LMIi (on–B/S)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' LMIi (on– and off–B/S)	0.212** (2.381)	0.124*** (2.934)	0.147** (2.450)			
Peers' LMIi (on–B/S)				0.200** (2.445)	0.120*** (2.991)	0.140** (2.538)
Peer group size	10	20	30	10	20	30
No. observations	9,960	9,960	9,960	9,960	9,960	9,960
No. banks	337	337	337	337	337	337
Bank characteristics	Y	Y	Y	Y	Y	Y
Peers avg. controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	16.94***	113.5***	81.62***	18.61***	118.6***	92.33***
First-stage instrument	-0.001*** (-4.116)	-0.003*** (-10.655)	-0.002*** (-9.035)	-0.001*** (-4.314)	-0.003*** (-10.892)	-0.002*** (-9.609)
Mean of dependent variable	-0.449	-0.449	-0.449	-0.451	-0.451	-0.451

The table reports two-stage least squares (2SLS) estimates of Model (1) using the quarterly U.S. sample of listed banks and the Bai, Krishnamurthy, and Weymuller (2018) on– and off–balance sheet and on–balance sheet Liquidity Mismatch Index (LMI) as the dependent variables. I reverse the signs of the LMI and express it as a share of total assets (LMIi) so that this measure is directly comparable to the Berger and Bouwman (2009) indicator. The summary statistics are presented in Table OA4 in the Online Appendix. The instrument is the Leary and Roberts (2014) lagged peer bank average equity return shock. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the United States in the same quarter grouped into a maximum of 10, 20, or 30 banks according to their size. Bank-specific characteristics include size, capital ratio, ROA, deposit share, and NPL provisions. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one quarter. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

liquidity creation, the results indicate that competitors' influence also does not operate via liquidity created off the balance sheet. Overall, consistent with Rajan (1994) and Uchida and Nakagawa (2007), these findings suggest that collective risk-taking operates through liquidity created on the asset side of banks' balance sheets, of which lending is a key component.[19]

[19]Table OA12 in the Online Appendix splits the asset side-component of liquidity creation into its earning asset and non-earning asset subcomponents and, in line with this finding, shows that peer effects are concentrated on the earning assets subcomponent of liquidity creation.

Table 7: Asset versus liability side of liquidity creation

	Asset-side LC			Liability-side LC		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' asset-side LC	0.047**	0.062***	0.064**			
	(2.462)	(3.007)	(2.096)			
Peers' liability-side LC				-0.004	0.029	0.048
				(-0.119)	(1.390)	(1.470)
Peer group size	10	20	30	10	20	30
No. observations	10,575	13,023	13,954	10,575	13,023	13,954
No. banks	1,407	1,528	1,584	1,407	1,528	1,584
No. peer groups	141	80	59	141	80	59
Bank, peer, and country controls	Y	Y	Y	Y	Y	Y
Year and bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	26.95***	17.91***	10.15***	7.449***	7.582***	1.619
First-stage instrument	0.014***	0.014***	0.009***	0.004***	0.006***	0.003
	(5.191)	(4.232)	(3.185)	(2.729)	(2.754)	(1.272)
Mean of dependent variable	0.154	0.165	0.169	0.150	0.148	0.147

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the asset and liability-side components of the Berger and Bouwman (2009) on–balance sheet liquidity creation (LC) measure divided by total assets as the dependent variables. All coefficients are scaled by the corresponding variable's standard deviation. t-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size (total assets). The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one period. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Cross-sectional Heterogeneity. What type of banks mimic their competitors? To examine whether some financial institutions are more sensitive to their peers' liquidity mismatch policies, I split banks into two groups according to the median of the within-country-year distribution of lagged values of bank-level measures capturing different dimensions of performance and risk. These include the Z-score (distance to default) as in Dam and Koetter (2012) or Beck, De Jonghe, and Schepens (2013), the Z-score's individual components (capital ratio, ROA, standard deviation of ROA), and banks' non-interest income share.[20] I then exploit the effect's

[20] The Z-score can be interpreted as the number of standard deviations by which returns would have to fall from the mean to eliminate all the equity of a bank, with a lower Z-score implying a higher probability of

cross-sectional heterogeneity by interacting the main explanatory variable of interest, peers' liquidity creation, with the two indicator variables (I_{Low} and I_{High}) associated with a given bank-level measure. All models are estimated by 2SLS where the two endogenous variables are the peer banks' average liquidity creation interacted with the two indicator variables, and the two instruments are the peers' parents liquidity creation interacted with the same two indicator variables—since each model now has two endogenous regressors, there are also two excluded instruments and two separate first-stage models. To avoid redundancy, the results reported are based on the benchmark peer group definition, where competitors are defined as other commercial banks operating in the same country in the same year and grouped into a local network of 20 banks according to their size.

The results reported in Table 8 show that the peer effects in banks' liquidity mismatch decisions are concentrated in banks that are ex ante riskier. Importantly, the two first-stage regressions in each of the models also show that (i) the instruments are correlated with the endogenous variables in a way that is consistent with what one would expect, and that (ii) the estimates do not seem to suffer from a weak instruments problem, with F-statistics and associated p-values computed following the procedure of Sanderson and Windmeijer (2016) to check for weak instruments in settings with more than one endogenous variable. In detail, this form of collective risk-taking behavior is not present in banks with ex ante higher profit stability and lower probability of default. The peer effects of interest are also not statistically significant for banks with higher capital ratios, a result consistent with theory showing that high capital strengthens banks' monitoring incentives (Mehran and Thakor, 2011) and lowers asset-substitution moral hazard (Morrison and White, 2005). Similarly, in Albuquerque, Cabral, and Guedes (2019) the incentive to use more relative performance evaluation and thus invest in correlated projects leading to systemic risk also increases with bank leverage. Finally, this finding also suggests that higher levels of funding liquidity risk are not being

default. In detail, the Z-score of bank i at time t is defined as the sum of return on assets (ROA) and the capital ratio (equity to assets), all divided by the standard deviation of the ROA using a three-year rolling window. This approach avoids the variation in Z-scores within banks over time to be exclusively driven by variation in levels of profitability and capital. Furthermore, by not relying on the full sample period, the denominator is no longer computed over different window lengths for different banks.

compensated with higher capital ratios that could increase a bank's probability of survival during the crisis (Berger and Bouwman, 2013).

Bank Size and Coordinated Behavior. Table 9 examines in more detail the potential channels driving the correlated balance sheet exposures. Specifically, banks are first classified as small or large by splitting the within country-year distribution of banks' total assets according to the median. The peer averages are then constructed based on: (i) small banks mimicking small banks and large banks mimicking large banks; or (ii) small banks mimicking large banks and large banks mimicking small banks. This analysis is useful not only to shed light on the potential mechanisms behind this type of coordinated behavior, but also to understand whether these decisions are indeed likely to be strategic.

The results confirm that the size of competitors is a crucial determinant for individual banks' decision-making. Specifically, the coefficient estimates indicate that large and small banks' liquidity mismatch decisions are only sensitive to choices of their respective counterparts.[21] In other words, as predicted by the theoretical literature on collective moral hazard due to the LOLR bailout commitment (e.g., Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012), larger banks tend to mimic other larger banks, while smaller banks follow other smaller banks. The results therefore suggest that learning (i.e., free-riding in information acquisition) is unlikely to play a major role in this setting since small banks' liquidity choices do not seem to be affected by the respective decisions of large banks. This differs from the findings of Leary and Roberts (2014) that consider a sample of listed non-financial firms in the United States and show that peer firm relevance is driven by a leader-follower model in which small firms are sensitive to large firms, but not vice versa. In contrast with other industries, however, the institutional framework (e.g., existence of government guarantees) and regulatory environment (e.g., strict regulations and guidelines on what the banks can and should do) of the banking

[21] In specifications with only one endogenous regressor (e.g., Columns 1 and 3 of Table 9), the Sanderson and Windmeijer (2016) F-statistic is equal to the Kleibergen and Paap (2006) F-statistic I report in Tables 2 to 7. While the peer groups in Column (1) of Table 9 are defined in a different manner than in the baseline analysis (that is, banks within a country-year pair split into two size groups, where each group can have any number of banks versus banks within a country-year pair grouped into groups of 10, 20, and 30 banks of similar size), it is reassuring that the coefficient estimate is similar in magnitude to those in Table 2.

sector arguably make it less likely for rational "herding" driven by small banks' uncertainty regarding the optimal liquidity mismatch policy to occur.

Additionally, the estimate in Column (2) of Table 9 shows that such mimicking behavior is relatively stronger among larger banks. This is consistent with large banks taking more risk than small banks in equilibrium since they internalize that their decisions directly affect the government's optimal bailout policy (Dávila and Walther, 2018), but also with risk-taking being driven by the presence of RPE in compensation schemes that tends to be more prevalent in larger banks (Ilic, Pisarov, and Schmidt, 2017; Albuquerque, Cabral, and Guedes, 2019).[22] This finding is particularly important given that the trade-off between liquidity creation and fragility is most consequential for large banks that create the most liquidity (Berger and Bouwman, 2009).

4.3 Collective Risk-taking and Financial Sector Stability

Asymmetric Behavior. To investigate the impact peer effects may have on financial sector stability, I start by examining whether the response of individual banks to the liquidity mismatch choices of competitors is asymmetric. In other words, this analysis aims to understand if this type of mimicking behavior is stronger when peers are increasing liquidity transformation risk rather than decreasing it. In fact, if banks follow competitors with the same intensity when they are decreasing and increasing risk, the impact of such coordinated behavior on financial stability is likely to be small. To answer this question, I interact the main explanatory variable as well as the instrument with (i) a dummy variable equal to 1 if peers' average liquidity creation decreased from periods $t-1$ to t, a 0 otherwise; and (ii) a dummy variable equal to 1 if peers' average liquidity creation increased from periods $t-1$ to t, and 0 otherwise.

[22] Dávila and Walther (2018) show theoretically that since risky choices by large banks also increase the implicit bailout subsidy for the banking sector as a whole, small banks may also increase risk-taking beyond what they would optimally choose in the absence of large banks. In contrast, Bonfim and Kim (2019) find small banks actually decrease liquidity risk when large banks are increasing it, although this result is not consistent across different specifications. Empirically, and after providing a rigorous econometric treatment for the endogeneity of peer effects, I find no consistent evidence of strategic spillovers to small banks. In fact, although positive in terms of magnitude, the coefficient estimate in Column 4 of Table 9 (capturing small banks mimicking large banks) is statistically insignificant from zero.

Table 8: Cross-sectional heterogeneity

Liquidity creation	Capital ratio	Profitability (ROA)	Non-interest income share	Profit stability (-sd[ROA])	Distance to default (Z-score)
	(1)	(2)	(3)	(4)	(5)
Peers' LC $\times I_{Low}$	0.081***	0.066***	0.068***	0.079***	0.082***
	(4.066)	(3.552)	(3.632)	(4.093)	(4.161)
Peers' LC $\times I_{High}$	0.041	0.078***	0.072***	0.028	0.028
	(1.567)	(2.978)	(2.802)	(0.760)	(0.867)
No. observations	13,023	13,023	13,023	9,794	9,794
No. banks	1,528	1,528	1,528	1,290	1,290
No. peer groups	80	80	80	78	78
Bank, peer, and country controls	Y	Y	Y	Y	Y
Year and bank FE	Y	Y	Y	Y	Y
Mean of dependent variable	0.313	0.313	0.313	0.323	0.323

First-stage regressions	Peers' LC $\times I_{Low}$	Peers' LC $\times I_{High}$	Peers' LC $\times I_{Low}$	Peers' LC $\times I_{High}$	Peers' LC $\times I_{Low}$	Peers' LC $\times I_{High}$	Peers' LC $\times I_{Low}$	Peers' LC $\times I_{High}$	Peers' LC $\times I_{Low}$	Peers' LC $\times I_{High}$
	(1.1)	(1.2)	(2.1)	(2.2)	(3.1)	(3.2)	(4.1)	(4.2)	(5.1)	(5.2)
First-stage instrument 1: Peers' parents LC $\times I_{Low}$	0.018***	0.000	0.018***	0.000	0.018***	0.000	0.018***	0.000	0.018***	0.000
	(4.293)	(0.102)	(3.900)	(0.024)	(4.163)	(0.051)	(3.787)	(0.202)	(3.660)	(0.219)
First-stage instrument 2: Peers' parents LC $\times I_{High}$	-0.002	0.021***	0.003	0.017***	-0.001	0.022***	0.000	0.015**	0.000	0.016**
	(-0.414)	(2.979)	(0.614)	(3.047)	(-0.239)	(3.139)	(0.022)	(2.311)	(0.020)	(2.551)
First-stage SW F-Stat	18.49***	10.49***	16.00***	13.58***	17.33***	12.23***	14.70***	9.68***	13.86***	11.67***

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bouwman (2009) on–balance sheet liquidity creation measure (LC) divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. Banks are split into two groups (I_{Low} and I_{High}) according to the median of the within-country-year distribution of lagged values of banks' capital ratio (equity/assets), ROA (net income/assets), non-interest income share (non-interest income/total income), profit stability (standard deviation of the ROA using a three-year rolling window), and distance to default (Z-score). To avoid redundancy, the results reported are based on the benchmark peer group definition as in specification (3) of Table 2 where competitors are defined as other commercial banks operating in the same country in the same year, and grouped into a network of 20 banks according to their size. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. First-stage SW F-stat is the Sanderson and Windmeijer (2016) conditional first-stage F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 9: Bank size and coordinated behavior

Liquidity creation	Small → small & large → large		Small → large & large → small	
	(1)	(2)	(3)	(4)
Peers' LC	0.084***		0.035	
	(6.380)		(1.392)	
Peers' LC × I_{Small}		0.076***		0.015
		(3.942)		(0.275)
Peers' LC × I_{Large}		0.093***		0.055
		(5.653)		(0.818)
No. observations	14,099	14,099	14,202	14,202
No. banks	1,587	1,587	1,601	1,601
No. peer groups	60	60	60	60
Bank, peer, and country controls	Y	Y	Y	Y
Year and bank FE	Y	Y	Y	Y
Mean of dependent variable	0.310	0.310	0.312	0.312

First-stage regressions	Peers' LC	Peers' LC × I_{Small}	Peers' LC × I_{Large}	Peers' LC	Peers' LC × I_{Small}	Peers' LC × I_{Large}
	(1.1)	(2.1)	(2.2)	(3.1)	(4.1)	(4.2)
First-stage intrument: Peers' parents LC	0.026***			0.006		
	(5.281)			(1.397)		
First-stage instrument 1: Peers' parents LC × I_{Small}		0.020***	0.003		0.008	0.002
		(3.936)	(1.157)		(1.561)	(0.676)
First-stage instrument 2: Peers' parents LC × I_{Large}		0.004	0.027***		-0.001	0.001
		(0.983)	(3.279)		(-0.327)	(0.238)
First-stage SW F-Stat	27.89***	16.75***	10.06***	1.951	0.114	0.076

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bouwman (2009) on–balance sheet liquidity creation measure (LC) divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. Banks are split into two groups (I_{Small} and I_{Large}) according to the median of the within-country-year distribution of banks' total assets. The peer averages are then constructed based on: (i) small banks mimicking small banks and large banks mimicking large banks; or (ii) small banks mimicking large banks and large banks mimicking small banks. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. First-stage SW F-stat is the Sanderson and Windmeijer (2016) conditional first-stage F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 10: Asymmetric behavior

Liquidity creation	(1)	(2)	(3)
Peers' LC × $I_{LC\uparrow}$	0.069***	0.086***	0.104***
	(3.172)	(4.109)	(4.590)
Peers' LC × $I_{LC\downarrow}$	0.030	0.046	0.043
	(0.746)	(1.630)	(0.901)
No. observations	10,575	13,023	13,954
No. banks	1,407	1,528	1,584
No. peer groups	141	80	59
Bank, peer, and country controls	Y	Y	Y
Year and bank FE	Y	Y	Y
Mean of dependent variable	0.304	0.313	0.316

First-stage regressions	Peers' LC × $I_{LC\uparrow}$	Peers' LC × $I_{LC\downarrow}$	Peers' LC × $I_{LC\uparrow}$	Peers' LC × $I_{LC\downarrow}$	Peers' LC × $I_{LC\uparrow}$	Peers' LC × $I_{LC\downarrow}$
	(1.1)	(1.2)	(2.1)	(2.2)	(3.1)	(3.2)
First-stage instrument 1:	0.016***	-0.005	0.014**	-0.001	0.016**	-0.003
Peers' parents LC × $I_{LC\uparrow}$	(3.357)	(-1.505)	(2.504)	(-0.346)	(2.463)	(-0.568)
First-stage instrument 2:	-0.000	0.016***	0.001	0.019***	-0.000	0.017***
Peers' parents LC × $I_{LC\downarrow}$	(-0.006)	(3.079)	(0.189)	(3.368)	(-0.051)	(2.862)
First-stage SW F-Stat	16.96***	17.18***	10.19***	17.08***	8.39***	14.99***

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bouwman (2009) on–balance sheet liquidity creation measure (LC) divided by total assets as the dependent variable. Table OA2 in the Online Appendix presents the weights given to the different balance sheet items when computing this measure. The main explanatory variable capturing the average liquidity created by competitors is interacted with (i) a dummy variable $I_{LC\uparrow}$ equal to 1 if peers' average liquidity creation increased from periods *t-1* to *t*, a 0 otherwise; and (ii) a dummy variable $I_{LC\downarrow}$ equal to 1 if peers' average liquidity creation decreased from periods *t-1* to *t*, and 0 otherwise. All coefficients are scaled by the corresponding variable's standard deviation and *t*-statistics (in parentheses) are robust to heteroskedasticity and within-peer-group dependence. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank *i*. All control variables are lagged by one period. First-stage SW F-stat is the Sanderson and Windmeijer (2016) conditional first-stage F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 10 reports the findings. The results show that correlated liquidity transformation activities do work asymmetrically, with individual banks mimicking their respective peers only when competitors are increasing risk. Further validating the paper's identification strategy, the instruments are also correlated with the endogenous variables in the way one would expect:

while local banks behave strategically and mimic their respective peers only when competitors are increasing liquidity creation, a foreign-owned subsidiary considers the liquidity mismatch policy of its parent when the parent is both increasing and decreasing liquidity risk.[23]

Overall, the results suggest that banks' liquidity policies are strategically determined according to the behavior of their competitors, which can ultimately lead to financial instability due to increased liquidity transformation risk in the banking system. Diamond and Rajan (2001) and Allen and Gale (2004), for instance, argue that banks' liquidity transformation activities are a fundamental driver of fragility and suggest that bank failures are more likely to occur when the level of liquidity creation is high. Rajan (1994) and Acharya and Naqvi (2012) find that banks creating excessive liquidity also tend to engage in lending practices leading to asset bubbles, which ultimately result in future financial instability. Berger and Bouwman (2017) also show that banking crises in the United States have been preceded by periods of abnormal liquidity creation. In a different context, Hong, Huang, and Wu (2014) show that systemic liquidity risk as measured by TED spreads was a major predictor of bank failures in 2009 and 2010, while Cai, Eidam, Saunders, and Steffen (2018) analyze syndicated loans to firms in the United States and show that a larger overlap of banks' loan portfolio makes them greater contributors to systemic risk and that interconnectedness increases aggregate systemic risk during recessions.

Peer effects and Bank Risk. As a final step, I examine the consequences of strategic liquidity mismatch choices explicitly—that is, whether such correlated balance sheet exposures have an adverse effect on both individual banks' default risk and overall systemic risk. Compared with Model (1), the relationship between the liquidity mismatch position of bank i and that of its peers is now allowed to vary not only across countries, but also over time following the

[23]These findings also help to reassure that the baseline results are unlikely to be driven by changes in prudential regulations introduced after the crisis or by the Basel's first guidelines on the new liquidity regulations issued in 2010. First, changes in the intensity of capital requirements, interbank exposure limits, concentration limits, LTV ratios limits, and reserve requirements are explicitly controlled for in the model following Cerutti, Correa, Fiorentino, and Segalla (2017). Second, these changes in regulation would imply that all banks adjust their portfolio towards reducing liquidity transformation risk. However, as the results in Table 10 show, such collective strategic behavior is asymmetric, with individual banks mimicking their respective peers only when competitors are increasing funding liquidity risk.

framework of Albuquerque, Cabral, and Guedes (2019) and Denbee, Julliard, Li, and Yuan (2018). To capture time and country-varying peer effects in liquidity mismatch decisions, $\beta_{j,t}$, I shock the average peer effect in the overall sample with a country-year indicator variable $I_{j,t}$ and estimate the following model separately for each country-year combination:

$$y_{i,j,t} = \mu_i + (\beta_0 + \beta_1 I_{j,t})\bar{y}_{-i,j,t} + \lambda' \bar{X}_{-i,j,t-1} + \gamma' X_{i,j,t-1} + \delta' Z_{j,t-1} + v_t + \varepsilon_{i,j,t} \quad (4)$$

where i, j, and t correspond to bank, country, and year, respectively.[24] The estimated coefficient on the peer effect of interest, $\hat{\beta}_{j,t}$, is then used to run the following specification to gauge the impact of peer effects in liquidity choices on financial stability:

$$STA_{i,j,t} = \kappa + \delta\hat{\beta}_{j,t} + \gamma' X_{i,j,t-1} + \eta' Z_{j,t-1} + \mu_i + v_t + u_{i,j,t} \quad (5)$$

where $STA_{i,j,t}$ is either the distance-to-default (ln[Z-score]) when using a three or five-year window to compute the standard deviation of ROA, or the marginal expected shortfall—MES (Acharya, Pedersen, Philippon, and Richardson, 2017) and systemic capital shortfall—SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2017). MES is computed using the opposite of returns such that the higher a bank's MES is, the higher its systemic risk contribution. The market is defined as the country-specific banking sector equity market. SRISK corresponds to the expected bank i's capital shortage (in billion USD) during a period of system distress and severe market decline. Following Acharya, Engle, and Richardson (2012), the long-run MES is approximated as 1-exp(-18*MES) where MES is the one day loss expected if market returns are less than -2%. Unlike MES, SRISK is a also function of the bank's book value of debt, its market value of equity and a minimum capital ratio. To ensure comparability across countries, I follow Engle, Jondeau, and Rockinger (2015) and set the prudential capital ratio to 4% for banks reporting under IFRS and to 8% for all other accounting standards, including U.S. GAAP.

[24]For each of the separate regressions corresponding to each country-year combination $I_{j,t}$, there are again two endogenous regressors and two excluded instruments. I use the estimated coefficient on the peer effect for a given country-year pair as a regressor to explain bank risk if and only if the Sanderson and Windmeijer (2016) conditional first-stage F-statistics are above the weak instrument critical values proposed by Stock and Yogo (2005) based on size distortions of the associated Wald statistic considering a 25% maximal IV size.

The results reported in Tables OA13 and OA14 provide direct and thus novel empirical evidence that strategic complementarity in banks' liquidity mismatch policies decrease the stability of the financial system. In fact, as initially hypothesized, the estimated coefficients indicate that peer effects in liquidity mismatch policies are positively associated with individual banks' default risk and overall systemic risk. Importantly, this effect is both statistically and economically significant. Irrespective of the multitude of channels that have been put forward to explain this type of risk-taking behavior, these findings highlight the need of having a macroprudential tool that minimizes the propensity for banks to create excessive liquidity and collectively underprice liquidity risk. Such a binding requirement would allow for more efficient systemic liquidity risk management that would ultimately reduce the potential taxpayer burden.

5 Conclusion

The 2007–2009 financial crisis distinctly exposed the negative implications of excessive liquidity transformation for financial sector stability and the macroeconomy. This outcome was achieved in part through banks' correlated exposures. Ultimately, liquidity mismatch decisions of individual banks spilled over to other financial institutions and markets, exacerbating losses and overall liquidity stress. Such systemic liquidity risk was, judging by the extent of government intervention during the crisis, clearly understated by both the private and public sectors. In this regard, this paper examines empirically the extent to which banks' liquidity transformation activities are affected by the choices of their competitors and the impact of these collective risk-taking decisions on financial stability.

Using a novel identification strategy exploiting the presence of partially overlapping peer groups, I show that financial institutions incorporate their peers' liquidity mismatch decisions when determining their own. This strategic behavior is driven by liquidity created on the asset side, of which lending is a key component, and is concentrated in ex ante riskier banks. With respect to the consequences of such strategic behavior for the financial system, I first show that the response of individual banks to the liquidity mismatch choices of competitors is asymmetric, with individual banks mimicking their peers only when competitors increase liquidity transformation risk. I then show that peer effects in financial institutions' liquidity mismatch policies increase both individual banks' default risk and overall systemic risk. This effect is both statistically and economically significant, highlighting the importance of explicitly regulating systemic liquidity risk from a macroprudential perspective.

In fact, while the Basel III liquidity requirements, combined with improved supervision, should help to strengthen individual banks' funding structure and thus enhance banking sector stability, these liquidity standards are fundamentally microprudential in nature.[25] Despite the proposals for macroprudential liquidity regulation such as time-varying LCR and NSFR ratios or a macroprudential liquidity buffer where each bank would be required to hold assets that are systemically-liquid (IMF, 2011), policymakers and regulators have yet to establish a concise macroprudential framework that mitigates the possibility of a simultaneous liquidity need by financial institutions. Since information spillovers are a defining characteristic of panics due to financial agents' imperfect knowledge regarding common exposures and given that, as shown in this paper, these information spillovers between banks do occur, a static and time-invariant microprudential liquidity requirement that mainly depends on individual banks' idiosyncratic risk (rather than system-wide conditions) may not be suitable to prevent a systemic liquidity crisis. As argued by Dewatripont, Rochet, and Tirole (2010), "a 1 percent probability of failure means either that 1 percent of the banks fail every year or, alternatively, that the whole banking system fails every hundred years—quite distinct outcomes. Therefore it is crucial for regulators to find ways of discouraging herding behavior by banks."

[25] Most developed economies have recently introduced formal bank bail-in regimes that involve the participation of bank creditors in bearing the costs of restoring a distressed bank and that include heavy restrictions on taxpayer support. Despite the potentially negative but limited short-term costs of bail-ins for the real economy (Beck, Da-Rocha-Lopes, and Silva, 2018), this new resolution tool represents an important step to mitigate the incentives for collective risk-taking behavior. On the other hand, while the Financial Stability Board (FSB) issued in 2009 the core principles for the design of pay structures currently being implemented in different countries, Albuquerque, Cabral, and Guedes (2019) argue that these largely omit the role RPE plays in creating systemic risk.

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Online Appendix

Strategic Liquidity Mismatch and Financial Sector Stability

André F. Silva

Federal Reserve Board

A. Computation of the stock return shock

To extract the idiosyncratic component of stock returns, I follow Leary and Roberts (2014) by using, in addition to the market factor traditional in asset pricing models, an industry factor to remove any common variation in returns across the same peer group. The model is specified as follows:

$$R_{i,j,t} = \alpha_{i,j,t} + \lambda_{i,j,t}\left(RM_{j,t} - Rf_{j,t}\right) + \phi_{i,j,t}\left(\bar{R}_{-i,j,t} - Rf_{j,t}\right) + \epsilon_{i,j,t} \tag{6}$$

where $R_{i,j,t}$ refers to the stock return for bank i in country j over period t, $(RM_{j,t} - Rf_{j,t})$ is the excess market returns (i.e., market factor), and $\left(\bar{R}_{-i,j,t} - Rf_{j,t}\right)$ is the excess return on an equally-weighted portfolio excluding bank i's return (i.e., industry factor). The intercept $\alpha_{i,j,t}$ measures the mean monthly abnormal return. I use the one-month U.S. Treasury bill rate to proxy for the risk-free rate and the MSCI equity market index of each country to proxy for their respective market factor. The model is estimated for each bank in a rolling regression using a minimum of 24 and a maximum of 60 past monthly returns. In detail, to compute expected and idiosyncratic returns of bank i in month m of year t, I first estimate equation (6) using monthly returns from month m of year $t-5$ to month $m+12$ of year $t-1$. Using the estimated coefficients and the factor returns from bank i in month m of year t, the idiosyncratic return component, $\hat{\eta}_{i,j,t}$, is computed as the difference between the actual return $R_{i,j,t}$ and the expected return $\hat{R}_{i,j,t}$:

$$\hat{R}_{i,j,t} = \hat{\alpha}_{i,j,t} + \hat{\lambda}_{i,j,t} \left(RM_{j,t} - Rf_{j,t}\right) + \hat{\phi}_{i,j,t} \left(\bar{R}_{-i,j,t} - Rf_{j,t}\right) \tag{7}$$

and,

$$\hat{\eta}_{i,j,t} = R_{i,j,t} - \hat{R}_{i,j,t} \tag{8}$$

The idiosyncratic return obtained from the above model is therefore the return of the bank after removing all known sources of systematic variation. Thus, the residuals obtained from (6) should be purely bank specific and hence free from any commonalities across the bank. To ensure consistency with the frequency of accounting data, I compound the monthly idiosyncratic return component to have an annual measure. This quantity is then averaged over the peer banks for each country j in each year t, and the exogenous source of variation for peer banks' liquidity choices is the lagged average peer bank equity return shock.

B. Additional tables and results

Table OA1: Reported peer groups of the largest U.S. banks

	Wells Fargo	JPMorgan Chase	Citigroup	U.S. Bancorp	PNC	BNY Mellon	State Street	Capital One
American Express	X	X	X					X
Bank of America	X	X	X	X	X			X
BNY Mellon	X		X				X	
BB&T	X			X	X			X
Capital One	X		X		X		X	
Citigroup	X	X						X
Fifth Third	X			X	X			X
Goldman Sachs	X	X	X				X	
JPMorgan Chase	X		X	X	X	X	X	X
KeyCorp	X			X	X			
Morgan Stanley	X	X	X			X	X	
PNC	X		X	X		X	X	X
Regions	X			X	X			X
State Street	X					X		
SunTrust	X			X	X			X
U.S. Bancorp	X		X		X	X	X	X
Wells Fargo		X	X	X	X	X	X	X
AIG			X					
MetLife			X					
Prudential			X			X		
M&T Bank					X			
BlackRock						X	X	
Franklin Resources						X	X	
Charles Schwab						X		
Northern Trust						X	X	
Ameriprise							X	
Discover								X
Total No. Peers	16	6	13	9	11	11	12	12

This table presents the peer groups of the largest banks operating in the Unites States in 2016 as reported in their publicly-available 2017 proxy statements. These comprise both financial performance peers and labor market peers. The former includes other banks directly competing for financial capital and customers, and that match the respective bank's scope, scale, business model/mix, and geography. The latter also includes banks that directly compete for executive talent.

Table OA2: Liquidity Creation and NSFR weights

ASSETS	***Liq.***	***Creation***	***RSF***	**LIABILITIES**	***Liq.***	***Creation***	***ASF***
Residential Mortgage Loans	0	Semi-liquid	85%	Customer Deposits – Current	0.5	Liquid	90%
Other Mortgage Loans	0.5	Illiquid	85%	Customer Deposits – Savings	0	Semi-liquid	95%
Other Consumer/Retail Loans	0	Semi-liquid	85%	Customer Deposits – Term	0	Semi-liquid	95%
Corporate & Commercial Loans	0.5	Illiquid	85%	Deposits from Banks	0.5	Liquid	0%
Other Loans	0.5	Illiquid	85%	Other Deposits & ST Borrowings	0.5	Liquid	0%
Loans and Advances to Banks	0	Semi-liquid	15%	Long Term Funding	-0.5	Illiquid	100%
Government Securities	-0.5	Liquid	5%	Derivatives	0.5	Liquid	0%
Derivatives	-0.5	Liquid	50%	Trading Liabilities	0.5	Liquid	0%
At-equity Investments in Associates	0.5	Illiquid	100%	**Total Funding**			
Trading Securities	-0.5	Liquid	50%	Other liabilities	-0.5	Illiquid	0%
Other Securities	-0.5	Liquid	50%	**Total Non-interest Bearing Liabilities**			
Other Earning Assets	0.5	Illiquid	100%	***Total Liabilities***			
Total Earning Assets							
Cash and Due From Banks	-0.5	Liquid	0%				
Fixed Assets	0.5	Illiquid	100%	**EQUITY**	***Liq.***	***Creation***	***ASF***
Other Non-earning Assets	0.5	Illiquid	100%	Common Equity	-0.5	Illiquid	100%
Total Non-earning Assets				Other Equity	-0.5	Illiquid	100%
Total Assets				***Total Equity***			

This table presents the weights assigned to each bank balance sheet item to construct the Liquidity Creation and NSFRi measures. Liquidity Creation is the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets. NSFRi (inverse of the Net Stable Funding Ratio) is defined as the ratio of the required amount of stable funding (RSF) to the available amount of stable funding (ASF). "Other Non-earning Assets" includes Foreclosed Real Estate, Goodwill, Other Intangibles, Current Tax Assets, Deferred Tax Assets, and Discontinued Operations. "Other liabilities" comprises Credit Impairment Reserves and Other Reserves, Fair Value Portion of Debt, Deferred Liabilities, Discontinued Operations, Insurance Liabilities, and Current Tax Liabilities. "Long-Term Funding" includes Senior Debt Maturing after 1 Year, Subordinated Borrowing, and Pref. Shares and Hybrid Capital accounted for as Debt. "Other Equity" consists of Non-controlling Interest, Securities Revaluation Reserves, Foreign Exchange Revaluation Reserves, Fixed Asset Revaluations and Other Accumulated OCI, and Pref. Shares and Hybrid Capital accounted for as Equity. "Other Securities" includes Trading Securities and at FV through Income, Available for Sale Securities, Held to Maturity Securities, and Other Securities. "Other Earning Assets" comprises Investments in Property, Insurance Assets, and Other Earning Assets.

Table OA3: Additional summary statistics – OECD sample

Variables	N	Mean	SD	P25	P50	P75
Peer group size: 10 banks						
Peers' liquidity creation	10,575	0.298	0.137	0.221	0.308	0.388
Peers' NSFRi	10,575	1.014	0.272	0.830	0.967	1.151
Peers' size	10,575	8.299	2.018	6.675	8.248	9.775
Peers' capital ratio	10,575	0.102	0.049	0.066	0.093	0.124
Peers' ROA	10,575	0.006	0.007	0.003	0.006	0.010
Peers' deposit share	10,575	0.569	0.121	0.486	0.574	0.657
Peers' NPL provisions	10,575	0.004	0.004	0.001	0.003	0.006
Peers' liquidity ratio	10,575	0.079	0.059	0.033	0.059	0.109
Peers' cost-to-income	10,575	0.626	0.165	0.548	0.630	0.714
Peers' non-interest income share	10,575	0.377	0.132	0.288	0.371	0.453
Peer group size: 20 banks						
Peers' liquidity creation	13,023	0.308	0.121	0.237	0.319	0.388
Peers' NSFRi	13,023	1.013	0.223	0.855	0.984	1.128
Peers' size	13,023	8.304	1.877	6.872	8.368	9.676
Peers' capital ratio	13,023	0.102	0.042	0.074	0.096	0.121
Peers' ROA	13,023	0.006	0.006	0.003	0.006	0.010
Peers' deposit share	13,023	0.575	0.110	0.499	0.577	0.649
Peers' NPL provisions	13,023	0.004	0.004	0.002	0.003	0.006
Peers' liquidity ratio	13,023	0.079	0.058	0.035	0.059	0.109
Peers' cost-to-income	13,023	0.631	0.142	0.570	0.635	0.712
Peers' non-interest income share	13,023	0.371	0.114	0.295	0.372	0.442
Peer group size: 30 banks						
Peers' liquidity creation	13,954	0.311	0.115	0.240	0.323	0.388
Peers' NSFRi	13,954	1.007	0.206	0.870	0.981	1.105
Peers' size	13,954	8.291	1.758	7.078	8.262	9.594
Peers' capital ratio	13,954	0.102	0.039	0.076	0.096	0.121
Peers' ROA	13,954	0.006	0.006	0.003	0.006	0.010
Peers' deposit share	13,954	0.579	0.107	0.505	0.577	0.651
Peers' NPL provisions	13,954	0.004	0.004	0.002	0.003	0.006
Peers' liquidity ratio	13,954	0.078	0.056	0.036	0.059	0.108
Peers' cost-to-income	13,954	0.634	0.134	0.576	0.642	0.711
Peers' non-interest income share	13,954	0.370	0.108	0.297	0.377	0.433

This table presents summary statistics for the variables in the cross-country sample that includes 1,584 commercial banks operating in OECD countries from 1999 to 2014. Liquidity creation (LC) is the Berger and Bouwman (2009) on–balance sheet liquidity creation measure divided by total assets. NSFRi is the inverse of the Net Stable Funding Ratio. Table OA2 presents the weights given to the different balance sheet items when computing both measures. Bank-level characteristics include size (ln[total assets]), capital ratio (equity/assets), ROA (net income/assets), deposit share (deposits/assets), NPL provisions (loan loss provisions/assets), liquidity ratio (liquid assets/total assets), cost-to-income ratio (non-interest expense/gross revenues), and non-interest income share (non-interest income/total income). Peer banks' average characteristics are computed as the average across all banks within a certain peer group, excluding bank i. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size.

Table OA4: Summary statistics – U.S. sample

Variables	N	Mean	SD	P25	P50	P75
Liquidity mismatch indicators:						
Liquidity creation – on– and off–B/S	14,407	0.474	0.183	0.354	0.477	0.596
Liquidity creation – on–B/S	14,407	0.367	0.150	0.277	0.375	0.469
Liquidity creation – asset side	14,407	0.144	0.149	0.051	0.151	0.244
Liquidity creation – liability side	14,407	0.224	0.085	0.167	0.222	0.282
Liquidity creation – off–B/S	14,407	0.105	0.058	0.063	0.093	0.134
LMIi – on– and off–B/S	9,960	-0.449	0.161	-0.549	-0.465	-0.360
LMIi – on–B/S	9,960	-0.451	0.158	-0.549	-0.465	-0.362
Bank-level characteristics:						
Size	14,407	14.38	1.343	13.44	14.12	15.03
Capital ratio	14,407	0.095	0.022	0.080	0.092	0.106
ROA	14,407	0.005	0.008	0.002	0.005	0.009
Deposit share	14,407	0.783	0.082	0.733	0.797	0.843
NPL provisions	14,407	0.003	0.005	0.001	0.001	0.003

This table presents summary statistics for the main variables in the quarterly U.S. sample that includes 472 listed commercial banks operating in the United States from 1999:Q1 to 2014:Q4. Liquidity creation (LC) is the Berger and Bouwman (2009) on– and off–balance sheet and on–balance sheet liquidity creation measures divided by total assets. LMI is the Bai, Krishnamurthy, and Weymuller (2018) Liquidity Mismatch Index. I reverse the signs of the LMI and express it as a share of total assets (LMIi) so that this measure is directly comparable to the Berger and Bouwman (2009) indicator. Bank-level characteristics include size (ln[total assets]), capital ratio (equity/assets), ROA (net income/assets), deposit share (deposits/assets), and NPL provisions (loan loss provisions/assets).

Table OA5: Peer effects in banks' liquidity mismatch decisions – standard errors

Liquidity creation	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Standard errors clustered at the peer group level						
Peers' liquidity creation	0.055***	0.050***	0.069***	0.062***	0.088***	0.081***
	(2.905)	(2.478)	(4.370)	(3.648)	(4.946)	(4.031)
	[10,575]	[10,575]	[13,023]	[13,023]	[13,954]	[13,954]
Panel B: Standard errors clustered at the bank level						
Peers' liquidity creation	0.055***	0.050***	0.069***	0.062***	0.088***	0.081***
	(3.101)	(2.625)	(4.703)	(3.955)	(5.712)	(4.587)
	[10,575]	[10,575]	[13,023]	[13,023]	[13,954]	[13,954]
Panel C: Heteroscedasticity-consistent standard errors						
Peers' liquidity creation	0.055***	0.050***	0.069***	0.062***	0.088***	0.081***
	(3.755)	(3.167)	(6.311)	(5.203)	(8.031)	(6.298)
	[10,575]	[10,575]	[13,023]	[13,023]	[13,954]	[13,954]
Peer group size	10	10	20	20	30	30
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation. t-statistics are reported in parentheses and the no. of observations in brackets. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA6: Peer effects in banks' liquidity mismatch decisions – OLS estimates

Liquidity creation	(1)	(2)	(3)	(4)	(5)	(6)
Peers' liquidity creation	0.029***	0.028***	0.046***	0.044***	0.056***	0.054***
	(6.916)	(6.956)	(8.424)	(8.890)	(8.324)	(8.786)
Peers' size	0.008	0.010	0.008	0.008	0.005	0.007
	(1.044)	(1.135)	(0.767)	(0.971)	(0.544)	(0.667)
Peers' capital ratio	0.000	0.000	0.009	0.008	0.013*	0.012*
	(0.005)	(-0.009)	(1.379)	(1.272)	(1.691)	(1.796)
Peers' ROA	0.003	-0.001	-0.002	-0.004	0.004	0.003
	(0.939)	(-0.198)	(-0.578)	(-1.144)	(0.759)	(0.769)
Peers' deposit share	0.001	0.002	-0.004	-0.001	0.001	0.004
	(0.244)	(0.532)	(-0.685)	(-0.158)	(0.211)	(0.611)
Peers' NPL provisions	0.002	0.000	-0.001	-0.002	0.002	0.002
	(0.695)	(0.020)	(-0.377)	(-0.552)	(0.521)	(0.668)
Peers' liquidity ratio		0.004		0.002		0.004
		(1.231)		(0.517)		(0.814)
Peers' cost-to-income		-0.005		-0.003		0.000
		(-1.524)		(-0.826)		(-0.028)
Peers' non-interest income share		0.009***		0.010***		0.011***
		(2.742)		(2.734)		(2.696)
Peer group size	10	10	20	20	30	30
No. observations	10,575	10,575	13,023	13,023	13,954	13,954
No. banks	1,407	1,407	1,528	1,528	1,584	1,584
No. peer groups	141	141	80	80	59	59
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Mean of dependent variable	0.304	0.304	0.313	0.313	0.316	0.316

This table reports OLS estimates of Model (1) using the cross-country OECD sample and the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and *t*-statistics (in parentheses) are robust to heteroscedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank *i*. All control variables are lagged by one period. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA7: Peer effects in banks' liquidity mismatch decisions – robustness tests A

Liquidity creation	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Alternative peer group sizes						
Peers' liquidity creation	0.040*	0.036*	0.073***	0.067**	0.104***	0.096***
	(1.899)	(1.682)	(3.083)	(2.570)	(5.817)	(4.931)
	[7,329]	[7,329]	[12,198]	[12,198]	[14,492]	[14,492]
Peer group size	5	5	15	15	50	50
Panel B: Do not consider a foreign parent if its subsidiary is too small or too large						
(i) Do not exclude foreign parents						
Peers' liquidity creation	0.058***	0.052**	0.064***	0.056***	0.091***	0.085***
	(3.337)	(2.913)	(4.053)	(3.271)	(4.443)	(3.540)
	[12,066]	[12,066]	[13,887]	[13,887]	[14,438]	[14,438]
(ii) Exclude foreign parents if subsidiary is less than 1% or more than 25% of its size						
Peers' liquidity creation	0.055***	0.050**	0.070***	0.065***	0.089***	0.083***
	(2.789)	(2.417)	(4.505)	(3.796)	(5.498)	(4.472)
	[10,343]	[10,343]	[12,967]	[12,967]	[13,895]	[13,895]
(iii) Exclude foreign parents if subsidiary is less than 10% or more than 50% of its size						
Peers' liquidity creation	0.079***	0.082***	0.091***	0.090***	0.096***	0.095***
	(2.864)	(3.053)	(6.639)	(6.385)	(5.690)	(4.690)
	[3,731]	[3,731]	[6,081]	[6,081]	[7,893]	[7,893]
Peer group size	10	10	20	20	30	30
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and *t*-statistics (in parentheses) are robust to heteroscedasticity and within-peer-group dependence. The no. of observations are reported in brackets. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 5, 15, 10, 20, 30, or 50 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank *i*. All control variables are lagged by one period. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA8: Peer effects in banks' liquidity mismatch decisions – robustness tests B

NSFRi	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: NSFR as liquidity mismatch indicator						
Peers' NSFRi	0.223***	0.225***	0.151***	0.149***	0.129***	0.129***
	(2.668)	(2.645)	(3.011)	(2.834)	(3.428)	(3.378)
	[10,575]	[10,575]	[13,023]	[13,023]	[13,954]	[13,954]
Liquidity creation						
Panel B: Exclude banks operating in the US						
Peers' liquidity creation	0.063***	0.059***	0.080***	0.074***	0.103***	0.096***
	(2.951)	(2.652)	(4.569)	(4.004)	(5.192)	(4.447)
	[9,487]	[9,487]	[11,481]	[11,481]	[12,192]	[12,192]
Panel C: Exclude foreign-owned subsidiaries						
Peers' liquidity creation	0.046***	0.042**	0.067***	0.060***	0.087***	0.078***
	(2.870)	(2.507)	(4.608)	(3.955)	(5.314)	(4.165)
	[7,700]	[7,700]	[9,829]	[9,829]	[10,693]	[10,693]
Peer group size	10	10	20	20	30	30
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the NSFRi (inverse of the Net Stable Funding Ratio) and the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variables. Table OA2 presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroscedasticity and within-peer-group dependence. The no. of observations are reported in brackets. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA9: Peer effects in banks' liquidity mismatch decisions – robustness tests C

Liquidity creation	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged peers banks' liquidity creation						
Peers' liquidity creation	0.061***	0.058**	0.074***	0.067***	0.098***	0.094***
	(2.895)	(2.568)	(3.997)	(3.212)	(6.283)	(5.690)
	[10,371]	[10,371]	[12,873]	[12,873]	[13,876]	[13,876]
Panel B: No winsorizing of control variables						
Peers' liquidity creation	0.056***	0.052**	0.070***	0.064***	0.089***	0.082***
	(2.956)	(2.529)	(4.474)	(3.745)	(5.017)	(4.082)
	[10,575]	[10,575]	[13,023]	[13,023]	[13,954]	[13,954]
Panel C: Drop banks with asset growth above 75% in any of the years						
Peers' liquidity creation	0.065***	0.059***	0.065***	0.058***	0.075***	0.065***
	(3.054)	(2.622)	(4.088)	(3.338)	(3.980)	(3.004)
	[8,169]	[8,169]	[10,043]	[10,043]	[10,767]	[10,767]
Peer group size	10	10	20	20	30	30
Bank and country controls	Y	Y	Y	Y	Y	Y
Additional controls	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets as the dependent variable. Table OA2 presents the weights given to the different balance sheet items when computing this measure. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroscedasticity and within-peer-group dependence. The no. of observations are reported in brackets. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size. The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Additional bank and country controls include banks' liquidity ratio, cost-to-income ratio, and non-interest income share, as well as global integration, deposit insurance, and IFRS. Peer banks' average characteristics comprise the same set of bank-specific controls in a given specification, but are computed as the average across all banks within a certain peer group, excluding bank i. All control variables are lagged by one period. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA10: Asset versus liability side of liquidity creation – U.S. sample

	Asset-side LC			Liability-side LC		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' asset-side LC	0.051***	0.036**	0.032***			
	(2.631)	(2.387)	(2.841)			
Peers' liability-side LC				-0.028	-0.030	-0.131
				(-0.925)	(-0.987)	(-0.599)
Peer group size	10	20	30	10	20	30
No. observations	14,407	14,407	14,407	14,407	14,407	14,407
No. banks	472	472	472	472	472	472
Bank and peer controls	Y	Y	Y	Y	Y	Y
Quarter and bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	30.27***	55.02***	182.0***	3.570*	7.579***	0.527
First-stage instrument	-0.003***	-0.003***	-0.004***	0.001*	0.001***	0.000
	(-5.502)	(-7.418)	(-13.492)	(1.890)	(2.753)	(0.726)
Mean of dependent variable	0.144	0.144	0.144	0.224	0.224	0.224

The table reports two-stage least squares (2SLS) estimates of Model (1) using the quarterly U.S. sample of listed banks and the asset and liability-side components of the Berger and Bowman (2009) liquidity creation (LC) measure (both divided by total assets) as the dependent variables. The summary statistics are presented in Table OA4 in the Online Appendix. The instrument is the Leary and Roberts (2014) lagged peer bank average equity return shock. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroscedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the United States in the same quarter grouped into a maximum of 10, 20, or 30 banks according to their size. Bank-specific characteristics include size, capital ratio, ROA, deposit share, and NPL provisions. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one quarter. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA11: Peer effects in off–B/S liquidity creation decisions – U.S. sample

Off–balance sheet LC	(1)	(2)	(3)
Peers' off–balance sheet LC	-0.042	0.007	0.033
	(-0.772)	(0.086)	(0.770)
Peer group size	10	20	30
No. observations	14,407	14,407	14,407
No. banks	472	472	472
Bank and peer controls	Y	Y	Y
Quarter and bank FE	Y	Y	Y
First-stage KP F-stat	1.615	0.535	2.732*
First-stage instrument	0.000	0.000	-0.000*
	(1.271)	(0.732)	(-1.653)
Mean of dependent variable	0.105	0.105	0.105

The table reports two-stage least squares (2SLS) estimates of Model (1) using the quarterly U.S. sample of listed banks and the off–balance sheet component of the Berger and Bowman (2009) liquidity creation (LC) measure divided by total assets as the dependent variable. The summary statistics are presented in Table OA4 in the Online Appendix. The instrument is the Leary and Roberts (2014) lagged peer bank average equity return shock. All coefficients are scaled by the corresponding variable's standard deviation and t-statistics (in parentheses) are robust to heteroscedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the United States in the same quarter grouped into a maximum of 10, 20, or 30 banks according to their size. Bank-specific characteristics include size, capital ratio, ROA, deposit share, and NPL provisions. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one quarter. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA12: Earning asset versus non-earning asset components of liquidity creation

	Earning asset LC			Non-earning asset LC		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' earning asset LC	0.027**	0.066***	0.067*			
	(2.014)	(3.082)	(1.920)			
Peers' non-earning asset LC				0.008	0.001	0.004
				(1.445)	(0.049)	(0.225)
Peer group size	10	20	30	10	20	30
No. observations	10,575	13,023	13,954	10,575	13,023	13,954
No. banks	1,407	1,528	1,584	1,407	1,528	1,584
No. peer groups	141	80	59	141	80	59
Bank, peer, and country controls	Y	Y	Y	Y	Y	Y
Year and bank FE	Y	Y	Y	Y	Y	Y
First-stage KP F-stat	38.49***	17.18***	7.607***	7.239***	0.381	0.249
First-stage instrument	0.016***	0.013***	0.009***	0.001***	0.000	0.000
	(6.204)	(4.145)	(2.758)	(2.691)	(0.617)	(0.499)
Mean of dependent variable	0.149	0.160	0.164	0.005	0.005	0.006

This table reports two-stage least squares (2SLS) estimates of Model (1) using the cross-country OECD sample and the earning asset and non-earning asset components of the Berger and Bowman (2009) liquidity creation (LC) measure (both divided by total assets) as the dependent variables. All coefficients are scaled by the corresponding variable's standard deviation. t-statistics (in parentheses) are robust to heteroscedasticity and within-peer-group dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size (total assets). The bank-specific (size, capital ratio, ROA, deposit share, and NPL provisions) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. Peer banks' average characteristics comprise the same set of bank-specific controls but are computed as the average across all banks within a certain peer group, excluding bank i's observation. All control variables are lagged by one period. First-stage KP F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic testing for weak instruments. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table OA13: **Peer effects in banks' liquidity mismatch decisions and default risk**

	$\ln\text{Zscore}_{3y}$			$\ln\text{Zscore}_{5y}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer effect:	-0.793***	-0.675***	-0.635***	-0.451***	-0.487***	-0.526***
Liq. creation – $\widehat{\beta_{j,t}^{LC}}$	(-7.746)	(-5.257)	(-5.087)	(-5.520)	(-4.351)	(-4.386)
Peer group size	10	20	30	10	20	30
No. observations	8,192	10,352	11,139	6,366	7,892	8,592
No. banks	1,240	1,378	1,426	1,037	1,154	1,203
Adj. R-squared	0.470	0.473	0.469	0.610	0.618	0.610
Bank characteristics	Y	Y	Y	Y	Y	Y
Country controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Mean of dependent variable	3.672	3.684	3.673	3.317	3.325	3.313

This table reports coefficient estimates of Model (5) using the cross-country OECD sample and ln(Z-Score) as the dependent variable. The Z-score of bank i at time t is defined as the sum of return-on-assets (ROA) and the equity to assets ratio, all divided by the standard deviation of the ROA using a three or five-year rolling window. This approach avoids the variation in Z-scores within banks over time to be exclusively driven by variation in levels of profitability and capital. In addition, by not relying on the full sample period, the denominator is no longer computed over different window lengths for different banks. The peer effects in liquidity mismatch decisions are estimated with Model (4) ($\widehat{\beta_{j,t}^{LC}}$), where the relationship between the liquidity of bank i and the liquidity of its peers is allowed to vary across countries and over time. I use the estimated coefficient on the peer effect for a given country-year pair as regressor to explain bank risk if and only if the Sanderson and Windmeijer (2016) conditional first-stage F-statistics are above the weak instrument critical values proposed by Stock and Yogo (2005) based on size distortions of the associated Wald statistic considering a 25% maximal IV size. Liquidity creation is the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets. Table OA2 presents the weights given to the different balance sheet items when computing this measure. t-statistics (in parentheses) are robust to heteroscedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size (total assets). The bank-specific (size, deposit share, NPL provisions, liquidity ratio, cost-to-income ratio, and non-interest revenue share) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. All control variables are lagged by one period. *, **, and *** designate that the test statistic is significant at the 10%, 5%, and 1% levels.

Table OA14: Peer effects in banks' liquidity mismatch decisions and systemic risk

	MES			SRISK		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer effect:	0.785*	1.283***	0.944***	2.479**	2.781**	2.236**
Liq. creation – $\widehat{\beta^{LC}_{j,t}}$	(1.786)	(3.193)	(2.596)	(2.270)	(2.588)	(2.159)
Peer group size	10	20	30	10	20	30
No. observations	1,515	1,993	2,224	1,515	1,993	2,224
No. banks	224	269	282	224	269	282
Adj. R-squared	0.706	0.684	0.688	0.805	0.801	0.804
Bank characteristics	Y	Y	Y	Y	Y	Y
Country controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Mean of dependent variable	2.652	2.548	2.455	3.985	3.309	3.151

This table reports coefficient estimates of Model (5) using the cross-country OECD sample and the marginal expected shortfall (MES) or the systemic capital shortfall (SRISK) as the dependent variables. MES is defined as bank i's expected equity loss (in %) in year t conditional on the market experiencing one of its 5% lowest returns in that given year. It is computed using the opposite of returns such that the higher a bank's MES is, the higher its systemic risk contribution. The market is defined as the country-specific banking sector equity market. SRISK corresponds to the expected bank i's capital shortage (in billion USD) during a period of system distress and severe market decline. Following Acharya, Engle, and Richardson (2012), the long-run MES is approximated as 1-exp(-18*MES) where MES is the one day loss expected if market returns are less than -2%. Unlike MES, SRISK is a also function of the bank's book value of debt, its market value of equity and a minimum capital ratio that bank firm needs to hold. The peer effects in liquidity mismatch decisions are estimated with Model (4) ($\widehat{\beta^{LC}_{j,t}}$), where the relationship between the liquidity of bank i and the liquidity of its peers is allowed to vary across countries and over time. I use the estimated coefficient on the peer effect for a given country-year pair as regressor to explain bank risk if and only if the Sanderson and Windmeijer (2016) conditional first-stage F-statistics are above the weak instrument critical values proposed by Stock and Yogo (2005) based on size distortions of the associated Wald statistic considering a 25% maximal IV size. Liquidity creation is the Berger and Bowman (2009) on–balance sheet liquidity creation measure divided by total assets. Table OA2 presents the weights given to the different balance sheet items when computing this measure. t-statistics (in parentheses) are robust to heteroscedasticity and within bank dependence. Peer groups are defined as commercial banks operating in the same country in the same year grouped into a maximum of 10, 20, or 30 banks according to their size (total assets). The bank-specific (size, capital ratio, ROA, deposit share, NPL provisions, liquidity ratio, cost-to-income ratio, and non-interest revenue share) and country-level controls (GDP per capita, GDP growth volatility, concentration, and prudential regulation intensity) are all defined in Table 1. All control variables are lagged by one period. *, **, and *** designate that the test statistic is significant at the 10%, 5%, and 1% levels.