Collateral Reuse as a Direct Funding Mechanism in Repo Markets

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Abstract

This paper empirically studies the use of rehypothecation, or collateral reuse, as a direct funding mechanism for dealers. Using unique data from the Australian repo market between late-2006 and late-2013, it aims to test the proposition that dealers set a positive spread between the haircut of the initial source repo and the haircut of the subsequent reuse repo. Surprisingly, the paper finds strong evidence that haircut spreads are negative both in the cross-section (across dealers) and in the time-series (across market periods). Although there is marginal evidence that haircut spreads increase after a shock to the funding liquidity of dealers, the spreads nonetheless remain negative and therefore only provide a smaller capital loss. Overall, the results are consistent with the alternative explanation that dealers seeking to reuse collateral prefer immediacy and are not in a position to set preferable terms of trade.

Keywords: collateral, rehypothecation, debt markets
JEL Classification: G10, G12

1. INTRODUCTION

An important issue in the current global financial landscape of increasing collateralisation[1] is the novel practice of rehypothecation, or collateral reuse.[2] Since the 2011 failure of MF Global – a broker-dealer that speculated using client collateral – academics, media commentators and regulators alike have debated the merits of this practice and whether it should be restricted. While this debate remains largely speculative and untested, a broad macroeconomic trade-off has been identified in several theoretical models (Lee, 2013; Andolfatto et al., 2015; Maurin, 2015; Kahn and Park, 2015): on the one hand, collateral reuse increases risk and creates a new channel for contagion as collateral must be returned via a system of counterparties; on the other hand, collateral reuse leads to a more efficient use of otherwise-encumbered collateral, thereby increasing funding efficiency and avoiding scarcity problems (Singh, 2014a; Duffie et al., 2015).

More recently, a new theoretical strand has emerged that undertakes a microeconomic perspective by endogenizing the terms of collateral transactions (Infante, 2014; Eren, 2014), thereby facilitating a more intricate understanding of this practice. In the context of a repurchase agreement ('repo') market,[3] these models study a rehypothecation structure under which dealers intermediate between collateral providers and cash lenders. The crux of the models is that dealers set a positive haircut margin (or 'haircut differential') between the initial source repo and the secondary reuse repo. In effect, this margin provides a direct funding mechanism as it is associated with a positive net cash flow for the dealer at the initial

[1] For instance, one of the key intentions of over-the-counter (OTC) reform that member nations committed to at the 2009 G20 Summit in Pittsburgh is an increase in the amount of collateral held for reducing counterparty risk. These commitments have since been partially or completely implemented by most members, including U.S. (see *Dodd-Frank Act 2010*), Europe (see *MiFID II 2014* and *MiFIR 2014*) and Australia (by the Australian Securities and Investment Commission following the passage of Part 7.5A of the *Corporations Act 2001*). Also, under the third instalment of the Basel Accords (Basel III), banks are required to hold more collateral and will receive penalties for non-collateralisation of financial transactions.

[2] Although they are technically different (see Comotto, 2013), the terms "collateral reuse" and "rehypothecation" are used interchangeably to refer to the use of posted collateral in a source transaction to secure a separate transaction.

[3] Repos are effectively loans secured with financial collateral, typically a debt security. They present an interesting setting due to their dramatic growth over the past two decades, which reflects their increasing use for cash and security funding by a broad range of institutional market participants (see, e.g., Section 2.3 of Gorton and Metrick, 2012).

leg of the two repos. Eren (2014) further shows that the use of this funding mechanism is dependent on the scarcity of the dealers other funding sources: the haircut differential is increased after a shock to the funding liquidity of the dealer.

This paper provides the first empirical analysis of haircut differentials by using unique transaction data from the Australian repo market. The dataset is ideally suited for studying this issue for three reasons. First, although collateral reuse is not explicitly identified, the data contains detailed information including a masked participant identifier and a dealer identifier. Hence, an algorithm that is similar to that developed and applied in Fuhrer et al. (2015) is used to match repos by collateral; the dealer identifier allows for the analysis to be restricted to the relevant reuse chains where a dealer sits in the middle as an intermediary. Second, the Australian repo market is bilateral,[4] large,[5] and has no regulatory restrictions on rehypothecation. This implies that the economic forces in play are likely generalisable to other developed jurisdictions and can be empirically detected without being impeded by artificial, policy constraints. Third, the sample period is comprehensive and thereby allows for a thorough analysis across the cross-section and time-series: the sample covers the period before, during and after the 2007-09 Global Financial Crisis (GFC), and has a broad coverage of collateral including money market securities, Treasury bonds and semi-government bonds.

The paper has a dual aim. First, its primary focus is to test the conjecture that haircut differentials are actively used by dealers as a funding mechanism. More specifically, it examines the hypothesis that haircut differentials are unconditionally positive (Infante, 2014; Eren, 2014) and the hypothesis that haircut differentials increase following a shock to the funding liquidity of dealers. At a broad level, such an examination is crucial as there is no real-world evidence on this new theoretical funding channel, which has important

[4] Bilateral repos are to be distinguished from tri-party repos, which have a similar structure except that an intervening clearing bank collects the cash and security, and assesses the security to set and manage haircuts on a day-to-day basis. Since tri-party repos are not negotiated trade-by-trade, bilateral repo terms tend to be more flexible and responsive to economic conditions (Martin et al., 2014). Evidence of this differing responsiveness can be seen by the more immediate and larger shock suffered in bilateral repo markets (Gorton and Metrick, 2012) as opposed to tri-party repo markets (Krishnamurthy et al., 2014) during the GFC.

[5] Based on a survey of Australian securities dealers, Wakeling and Wilson (2010) estimate that the market value of outstanding repos in Treasury bonds and semi-government bonds as of 28 July 2010 is $55.5 billion.

implications not just for our understanding of the microstructural foundations of rehypothecation, but also potentially for our understanding of financial intermediaries and their behaviour during crisis periods. Second, it aims to provide an exploratory analysis of rehypothecation including unconditional summary measures and a probit analysis of the factors affecting the likelihood that a dealer rehypothecates received collateral. Such an analysis is important as empirical evidence on collateral reuse is rare and only aggregate, inaccurate proxies have thus far been estimated; to the authors' knowledge, the study of the Swiss franc repo market in Fuhrer et al. (2015) is the only paper to document rehypothecation using accurate transaction data. This exploratory analysis therefore complements Fuhrer et al. (2015) and assists regulators with better understanding the scope and properties of rehypothecation activity in repo markets.

Overall, the key results are surprising and inconsistent with the notion that collateral reuse is used as a direct funding mechanism. First, there is strong evidence that haircut differentials are actually *negative*, indicative of a net cash flow loss at the initial stage to dealers. Moreover, this result is robust across dealers and across market conditions, providing a strong rejection of the presumption that haircut differentials are positive. Second, although there is some evidence that haircut differentials increase after a funding shock, the increase is insufficient to cause a change in the sign of the haircut differential. Inconsistent with Eren (2015), it is therefore deduced that haircut spreads are not used to meet capital shortages when funding alternatives are scarce. Third, consistent with Fuhrer et al. (2015) and concerns among some commentators of a dip in rehyothecation (Singh, 2014a), the exploratory analysis showed that collateral reuse experienced a fairly sudden and permanent decline at the start of the GFC. This is consistent with the statement that collateral providers increasingly demanded segregation of their collateral during the GFC due to concerns about credit risk and the possibility that their collateral would not be returned.

The rest of this paper is structured as follows. Section 2 discusses the structure of a reuse chain and provides a detailed review of prior literature to develop the two testable hypotheses. Section 3 lists the data sources used and describes the construction of the main variables used for analysis. Section 4 outlines and justifies the two-stage Heckman correction model used to test the second hypothesis with an adjustment for self-selection bias. Section 5 presents the results and Section 6 concludes.

2. DEVELOPMENT OF HYPOTHESES

2.1 Definition of Reuse Chains

Figure 1 depicts the structure of a reuse chain for which the primary party is the dealer $P2$. At the initial leg, a source repo consists of party $P2$ lending party $P1$ cash C_1 in return for some collateral security. Assuming the value of the collateral security is V_1, the cash lent is defined with respect to the haircut H_1 as follows:

$$C_1 = V_1(1 - H_1)$$

To form a reuse chain, party $P2$ then rehypothecates the same collateral security and enters into a repo position with party $P3$, posting the collateral to borrow cash C_2. The amount of cash borrowed is similarly defined with respect to the haircut H_2. Although V_1 is approximately equal for the source repo and reuse repo, the dealer may strategically target a haircut differential $H_2 < H_1$ so that the reuse chain provides a positive net initial cash flow $C_2 - C_1 > 0$. Given the inverse relationship between $(C_2 - C_1)$ and $(H_2 - H_1)$, the haircut differential is more conveniently defined as $\Delta H = H_1 - H_2$ for ease of interpretation.

< INSERT FIGURE 1 >

At the closing leg of the reuse chain, party $P2$ returns the principal cash C_2 plus the accrued interest at the reuse repo rate R_2 to $P3$. Upon receiving the collateral, $P2$ then returns it to $P1$, who is obliged to pay back the principal cash C_1 plus the accrued interest at the source repo rate R_1. Ignoring the principal value of the repos, the net closing cash flow from the perspective of $P2$ is directly related to the difference between R_2 and R_1. Given the inverse relationship between the net interest received and $(R_2 - R_1)$, a repo rate differential variable is defined as $\Delta R = R_1 - R_2$ for similar reasons to ΔH above.

2.2 Broad Literature on Collateral Reuse

2.2.1 Theoretical: in a series of policy research papers that have been developed into a textbook (Singh, 2014a), Manmohan Singh presents the first analysis of rehypothecation. Singh and Aitken (2010) describe a specific structure of collateral reuse where a financial intermediary plays a central role: collateral received from hedge funds requiring cash for investment are posted to receive cash from money market mutual funds. Singh (2011) proposes that collateral has its own velocity and economic multiplier effect due to its ability to secure multiple transactions at the same time. Singh (2013) argues that a reduction in the rate at which collateral is reused – rather than a shortage in collateral stock *per se* – is a primary cause of continuing credit scarcity after the GFC. Singh and Stella (2012) further develop the collateral velocity concept by showing that the money multiplier is also adjusted upwards in the presence of rehypothecation; on this basis, they suggest that monetary aggregates including M2 should be expanded to account for collateral reuse. In light of the money multiplier effect, Singh (2014b) discusses the implications of collateral reuse for the conduct of monetary policy. Extending the liquidity effects discussed by Singh (2014a), Monnet (2011) suggests that by allowing the same piece of collateral to fund multiple transactions, rehypothecation lowers the funding liquidity needs of traders.

A developing strand of the literature studies the effect of rehypothecation on economic welfare in a general equilibrium setting. First, Bottazzi et al. (2012) study the interaction between repo markets and underlying securities markets in the presence of collateral reuse. A key prediction of their model is that collateral reuse leads to the repo rate becoming special and security prices increasing above their expected discounted cash flows. Second, Lee (2013) develops a model of collateral circulation in a repo market. He finds evidence of a tradeoff: on the one hand, smoother collateral circulation leads to a more liquid repo market, which increases investment and welfare via several multiplier effects; on the other hand, financial fragility can deteriorate as less idle capital is available for investment opportunities, and an inefficient repo run can arise via a feedback loop. Third, Andolfatto et al. (2015)

studies a model in which rehypothecation endogenously arises due to an asset shortage. They find that rehypothecation delivers welfare gains in a high inflation and high interest economy. The actual rate at which collateral is reused, however, is greater than the optimal rate, indicating a role for public policy. Fourth, Maurin (2015) extends Geanakoplos' (1996) limited-commitment, collateral model to allow for rehypothecation. He shows that in complete markets, collateral reuse is redundant. In incomplete markets, however, collateral reuse assists in freeing up encumbered collateral and relaxing collateral constraints, thereby strictly improving welfare; at the same time, rehypothecation generates fragility along credit chains when aggregate leverage is high. Most recently, Kahn and Park (2015) uses the two-player framework in Bolton and Oehmke (2014) to show that while rehypothecation leads to a greater flow of funds, it introduces the risk that collateral is not returned to the original owner for whom the asset may be more valuable than others. He also specifies conditions under which collateral reuse is socially optimal.

Upon assessment, the theoretical literature identifies a trade-off in the macroeconomic effects of collateral reuse. On the one hand, it is alleged to improve collateral circulation and ultimately funding efficiency. On the other hand, it increases systemic risk by creating a new channel for contagion when collateral must be returned via a chain of linked counterparties. Although research in this area remains scarce, it is important to recognise that this paper is only thematically – not substantively – related to this trade-off: it studies a specific form of collateral reuse as a funding mechanism, which is discussed in Section 2.3 and is microeconomic in nature.

2.2.2 Empirical: empirical studies in this area are scarce and tend to be based on potentially-inaccurate, aggregate proxy variables. These studies have typically aimed to estimate a summary measure referred to as the "reuse rate" – this is effectively the number of times that a collateral security is reused on average. First, Singh and Aitken (2009) report the amount of collateral eligible for re-use by the largest dealers from holdings data obtained from 10-Q filings. Second, recognising that pledged collateral is an off-balance-sheet item, Singh and Aitken (2010) study the balance sheet footnotes of banks reporting eligible collateral received and re-pledged to estimate the shadow banking system. For the hedge fund industry as a whole in late-2007, they find that collateral is used to secure four transactions on average, consistent with a reuse rate of three: they divide the total eligible collateral received by dealers (estimated as 40% of the total pledgable collateral from all sources of the largest 10 banks) by the source of collateral (estimated as $1 trillion from "market sources… [and] discussions"). Singh (2011) revises this figure downwards by 25%; he also finds that the reuse rate decreases to around 1.4 by end-2010, and likely further decreased by end-2011, consistent with an ongoing deleveraging process in global financial markets. Third, Kirk et al. (2014) use 10-Q and 10-K filings to estimate the fraction of pledged collateral received by dealers that is rehypothecated. Similar to Singh (2011), their time-series plot shows a substantial contraction in this fraction since the GFC. They also find that this fraction increases with the size of the dealer's collateral pool. Fourth, the International Swaps and Derivatives Association (2014) reports that in a survey of non-centrally-cleared OTC derivative trades, borrowers grant rehypothecation rights in 85% of government security trades and 55% of other security trades surveyed. Of these eligible trades, 52.9% and 54.5% are actually rehypothecated.

Despite the shortcomings of these aggregated, rough proxies, two recent papers that are particularly pertinent to this paper adopt a different approach. First, Fuhrer et al. (2015), which uses a similar dataset to this paper, conducts the "first systematic empirical study on the re-use of collateral". They present a method to identify rehypothecated collateral and apply it to trade data from the Swiss franc GC repo market over a period between March 2006 and June 2013. The authors find that the re-use rate is around 5% on average, but is significantly higher prior to, and significantly lower following, the GFC. Using a logit regression, the authors then find that collateral availability, market stress, and relationship quality all have a negative effect on the reuse rate, consistent with their expectations. A key reason for the dramatically lower reuse rate relative to prior estimates is that their data only accounts for collateral reuse for funding repo transactions.

Second, in a study of the Australian market funded by the RBA, Cheung et al. (2014) conduct a survey of the largest 20 securities dealers on their collateral activity in Treasury and semi-government bonds as at June 2014. They estimate the total source collateral as \$64 billion, which despite including currently actively-used securities under pledge, repo or security loan (of which dealers own around 73% outright), represents only a small portion of the outstanding supply. They also estimate the total collateral use as \$101 billion by adding the total source collateral to the total collateral that is repledged by dealers. Their estimated reuse rate based on a broader set of transactions than Fuhrer et al. (2015) is therefore 60%. On this basis, they suggest that collateral reuse increases the effective supply of Treasury and semi-government bonds from \$80 billion (equal to the active supply) to \$128 billion.

2.3 Literature on Collateral Reuse as a Direct Funding Mechanism

Rather than model rehypothecation from an aggregate perspective under which individual repo terms are exogenous, a recent strand of the literature models rehypothecation as a *direct* funding mechanism for dealers. Infante (2014) models rehypothecation using a similar structure to that proposed by Singh and Aitken (2009): a dealer forms an intermediation chain between prime brokerage clients supplying collateral and cash lenders supplying cash. Infante's game-theory framework endogenizes the repo rates and haircuts for both the source repo and reuse repo. Further assuming that dealers prefer cash at the initial leg – on the basis that immediate funds are more valuable than delayed funds as they help avoid liquidity shortfalls and finance other activities – he finds that dealers exploit their position by setting a difference in the haircut applied to the source repo and reuse repo. Equivalently, in terms of the definition in Section 2.1, ΔH is greater than zero. Infante shows that ΔH represents a positive initial cash flow to dealers, which he describes as "money for nothing" that can serve as an important source of funding when the dealer's need for liquidity increases. However, dealers with higher default risk are exposed to runs by collateral providers, manifested as a sharp decline in H_1 and consequently ΔH.

In a particularly relevant paper, Eren (2014) models a similar setup by considering a single dealer sitting between a continuum of competitive prime brokerage clients supplying collateral and a continuum of competitive cash lenders supplying cash. Eren assumes that H_2 is zero and that H_1 (as well as the size of the two repos, R_1 and R_2) is set by the dealer bank who makes take-it-or-leave-it offers. Crucially, these reuse chains are assumed to be a funding alternative to cash holdings and fire sales. Under a two-period equilibrium setup, he finds that ΔH is positive, but that it is larger when the funding liquidity of the dealer is relatively scarce. During normal periods, ΔH is low such that the dealer realises profits at the closing leg in the form of an interest rate spread. During distressed periods, ΔH is increased to cover the dealer's liquidity shortage. Eren also shows that ΔR is affected: as hedge funds become exposed to the risk of dealer bankruptcy during distressed periods, R_1 and by extension ΔR decline. In the analysis, ΔH and ΔR are also shown to depend on the total cash supplied to the reuse chain and on dealer competition.

2.4 Testable Hypotheses

This paper aims to test the following two primary hypotheses:

$Hyp1$: Dealers use reuse chains to obtain a positive initial cash flow by setting a positive haircut differential (i.e., $\Delta H > 0$).

$Hyp2$: Relative to normal periods, the haircut differential (ΔH) increases after a shock to the funding liquidity of dealer $P2$.

The first hypothesis is consistent with the proposition that reuse chains are a funding mechanism for dealers (Infante, 2014; Eren, 2014). The second hypothesis is consistent with Eren's (2014) prediction that this funding mechanism is more actively used when a dealer's funding alternatives are scarce.

3. DATA AND VARIABLES

3.1 Primary Data

The primary dataset – which was obtained in confidence from the Australian Securities Exchange (ASX) – includes all wholesale repos settled via the Austraclear debt settlement facility between 1 July 2006 and 31 December 2013. For each repo transaction, the following data is provided for *both* the initial leg and closing leg:[6] settlement ID, trade date, cash amount, face value of collateral, ISIN code of collateral, and the numerical identities of the borrower and lender. Linked to each ISIN code, the Austraclear dataset provides security characteristics including asset class, the name of the issuer, maturity date, issue date, and total face value issued; for coupon-paying securities, the dataset also identifies the coupon rate, coupon payment frequency, and ex-coupon period. At the beginning of each three-month interval, the dataset lists the numerical identities of all registered Austraclear participants. These lists have been cross-referenced: (a) internally to identify the Reserve Bank of Australia (RBA); and (b) with the table of government bond dealers available at the Australian Prudential Regulation Authority (2014) to identify dealer banks.[7] Apart from these identified parties, the dataset includes over 400 other unidentified institutional participants, including other banks and deposit-taking institutions (ADIs), management funds, insurance companies, and custodians.

Several filters are applied to construct the final dataset. First, only repos with collateral belonging to one of the following asset classes are included: wholesale money market securities (including Bank Accepted Bills and Certificates of Deposit), Treasury bonds, and semi-government bonds. This filter allows for the market value of collateral to be more accurately calculated since these asset classes are much more liquid and homogenous.[8] In any case, they account for the majority of total repo activity. Second, all repos that include the

[6] The raw data contains all repo legs without any matching or identification. A simple but intuitive repo algorithm was developed and applied to match each initial leg to a corresponding closing leg. The accuracy of the algorithm is likely very high since roughly 79% were matched with no alternatives (implying that they have close to 100% accuracy), and an overall matching success rate of over 96% was obtained. To reduce matching error, a variable δ is constructed for each repo as the difference between the repo rate and the prevailing interbank overnight cash rate; repos with the lowest 2% and highest 2% values for δ are then omitted. In any case, any remaining matching error is unlikely to be correlated with the key variable of interest (thereby inducing omitted variable bias) in the primary model below.

[7] 16 dealers were identified in total. These institutions are the largest financial intermediaries and can be assumed to be dealers in the repo market for the asset classes studied.

[8] By way of contrast, corporate bonds and floating-rate securities are more difficult to accurately price and, unlike the U.S., represent a small fraction of the entire Australian debt market. Treasury bills are excluded as they were not issued by the Australian Commonwealth Government for the first half of the dataset.

RBA are excluded. Although the terms of all Austraclear repos are agreed privately between the two respective parties, the RBA sets fixed terms-of-agreement and almost always acts as a cash provider. Hence, the terms underlying RBA repos are not freely negotiated and are therefore not directly affected by market variables. Third, only repos with a term (distance between the initial leg and closing leg) between one day and one week are included. Repos with an intraday term are excluded for two reasons: (i) from a technical standpoint, the standard repo rate formula is undefined if there is less than one day between the initial leg and closing leg; (ii) from an intuitive standpoint, non-RBA intraday repos are not attractive to dealers as they can borrow or lend with the RBA on an interest-free intraday basis. Longer-term repos are excluded to avoid any confounding term effects and because they represent a fairly small fraction of all repos. Fourth, the first 50 trade days in the sample are excluded to allow for several backward-looking variables to be constructed in the primary analysis. Finally, since the analysis focuses on reuse channels with a dealer as $P2$, only repos for which a dealer is the collateral receiver are included. Hence, the final dataset represents only source repos, with reuse repos linked to their corresponding source repo via the method in Section 3.2.

< INSERT FIGURE 2 >

The flowchart in Figure 2 outlines these filters and the effect on the sample size. In total, there is a roughly 70% reduction from 337,770 repos to 100,103 repos. It is important to note, however, that these filters are necessary to amend the raw dataset to a more meaningful form for analysis. Moreover, the final dataset is still large and its repo-by-repo nature allows for sufficient variation in the key variables and should therefore provide reasonable statistical power in the primary analysis.

3.2 Repo Variables

3.2.1 Repo Rates and Haircuts: consistent with the actual/365 convention used in the Australian market, the repo rate (R) and haircut (H) for each repo are defined as follows:

$$R = \left(\frac{C_2}{C_1} - 1\right) \times \frac{365}{t}$$

$$H = 1 - \frac{C_1}{V_1}$$

where C_1 is the principal cash amount borrowed in the initial leg, C_2 is the principal cash plus interest returned in the closing leg, V_1 is the market value of the security used as collateral at the time of the initial leg, and t is the term in days. Intuitively, R is the interest rate applied to the secured loan provided by the repo party, and H is the level of collateralisation applied (so that a higher H implies that more valuable collateral is required to secure every dollar borrowed or, equivalently, that less cash can be borrowed for a fixed value of collateral).

The above input variables are all readily available except for V_1, which is estimated using a different benchmarking process from the underlying security market data for each asset class. This trade-by-trade market data is collected from Austraclear, which also accounts for the majority of all secondary cash trades in the Australian debt.[9] First, for Treasury bonds, the median[10] cash price per $100 face value across all secondary cash trades for the same security and the same day as the initial leg is calculated. This benchmark cash price is then adjusted by the relative face value of the collateral to provide an estimate of V_1. Treasury-bond-days with less than five observations are omitted.

Second, for money market securities and semi-government bonds, a benchmark yield is calculated as a significant portion of securities are thinly-traded. This is achieved by taking the median yield[11] across all secondary trades in a characteristic group of similar securities on the same day as the initial leg. For money market securities, four maturity groups based on time-to-maturity are defined: less than 30 days, 30-44 days, 45-89 days, and greater than 89

[9] For a more thorough explanation of the Austraclear cash trade data, see Issa and Jarnecic (2015).

[10] The median is used, rather than the mean, because it is less sensitive to outliers and therefore tends to better reflect the typical yield on a trade day. In any case, the mean was used as a robustness check and qualitatively identical results were obtained for the primary analysis.

[11] The yield for each cash trade is calculated by replacing V_1 with the actual cash amount paid in either formula (3.1) or (3.2) below – whichever is relevant – and then solving the formula for y. Formula (3.1) has a closed-form solution, whereas formula (3.2) is solved iteratively using the Newton-Raphson method.

days. For semi-government bonds, six groups based on Macaulay duration are defined:[12] less than 180 days, 180-364 days, 1-2 years, 2-4 years, 4-6 years, and greater than 6 years. Repos that are matched to a group-day with less than 5 observations are omitted. V_1 is then calculated by inputting y into one of the following pricing formulas:[13]

$$V_1 = \begin{cases} F\left(\dfrac{1+c}{1+\left(\frac{d}{365}\right)y}\right) & (3.1) \\ F\left(\dfrac{1}{\left(1+\frac{y}{2}\right)^{2T}} + \displaystyle\sum_{i=1}^{n} \dfrac{c}{\left(1+\frac{y}{2}\right)^{2t_i}}\right) & (3.2) \end{cases}$$

where F is the face value of the security used as collateral, y is the benchmark yield, T is the time-to-maturity of the security in years, c is the coupon rate divided by the number of coupons paid per year, n is the number of coupon payments remaining, d is the number of calendar days between the date of the initial leg and the maturity date, and t_i is the time in years until the i^{th} coupon payment excluding the next coupon payment if the bond is currently trading ex-coupon. Formula (1) is used for money market securities (setting $c = 0$), and for semi-government bonds that entitle the purchaser to only one future cash flow (i.e., at maturity). The more general formula (2) is used for semi-government bonds that entitle the purchaser to more than one future cash flow.

3.2.2 Collateral Reuse: as the analysis focuses on each reuse channel in isolation, the final dataset of repos (say "Set 1") are all assumed to represent source repos with the dealer collateral *receiver* identified as party $P2$. A potential set of reuse repos (say "Set 2") are then constructed by taking the dataset after the application of Filter 4 (and before Filter 5 is applied) in Figure 2 and only including repos for which the collateral *provider* is a dealer. A matching algorithm is then used to determine whether the collateral underlying repos in Set 1 have been recycled by $P2$ to form a reuse channel. The approach is similar to Fuhrer et al. (2015), except that an additional security matching constraint is applied: the two repos being matched must be secured with collateral that has the same ISIN code *and* face value. An

[12] Duration implicitly accounts for both the time-to-maturity and the coupon rate, and is therefore a better benchmark for coupon-paying securities.
[13] Note that formula (2) is the same as the formula used by the RBA (2014) to price Treasury bonds.

iterative procedure is used to flag a reuse repo (from Set 2) as a potential match to a source repo (from Set 1) if it meets the following requirements:

- Identical ISIN code and face value of the collateral securing the source and reuse repo.
- Dealer collateral provider in the source repo is the same as the dealer collateral receiver in the reuse repo.
- The initial-leg date of the reuse repo occurs on or after the initial-leg date of the source repo, and the closing-leg date of the reuse repo occurs on or before the closing-leg date of the source repo.

The iterative procedure is performed as follows. Set 1 is first sorted by settlement ID (which is equivalent to sorting by the time that the repo is entered and scheduled for settlement, typically immediately, in Austraclear) so that the matching criteria can be applied sequentially. In each iteration, the selected reuse repo is removed from Set 2 for applying the matching criteria to the source repo in the next iteration. In some cases, multiple reuse repos are matched to a single source repo; the reuse repo that is selected minimises the difference between the settlement ID of the source and reuse repo.

For each reuse channel, the repo rate differential (ΔR) and the haircut differential (ΔH) are measured as the difference in the repo rate and haircut of the source repo versus the reuse repo as follows:

$$\Delta R = R_1 - R_2$$

$$\Delta H = H_1 - H_2$$

Although it is typically more natural to construct a difference variable by subtracting the initial value from the closing value, ΔR and ΔH are defined in the opposite direction to allow for a more intuitive interpretation: ΔR is the net interest income at the closing leg and ΔH is the immediate net cash flow injection at the initial leg (see Section 2.2).

As a relative summary measure of reuse activity in the repo market, the reuse rate (RR_t) is calculated for a given time period t from the set of source repos as follows:

$$RR_t = \frac{\sum dV}{\sum V}$$

where V denotes the market value of collateral underlying a given source repo, d is a dummy variable that indicates whether the given source repo can be linked to a reuse channel, and $\mathbb{Z}: \{0 \leq RR_t < 1\}$. This measure, which is usually analysed in various forms in the rehypothecation literature (see, e.g., Bottazzi et al., 2012; Fuhrer et al., 2015; Andolfatto et al., 2015), effectively provides the ratio of reuse activity to total repo activity.

3.3 Funding Liquidity Shock Variables

3.3.1 Individual Dealer Shock: the equity capital of each dealer P_2 is used to proxy for an individual shock to a dealer's funding liquidity. End-of-day equity prices, $P_{d,t}$, from the primary stock exchange of each dealer (generally located in the country of the global headquarters) are obtained from the Securities Industry Research Centre of Asia Pacific (SIRCA). Daily logarithmic returns, $r_{d,t}$, are then computed with an appropriate adjustment for dividends and capitalisation changes as follows:

$$r_{d,t} = \begin{cases} \ln\left(\frac{P_{d,t}}{P_{d,t-1}}\right) & normal\ days \\ \ln\left(\frac{P_{d,t} + D_t}{P_{d,t-1}}\right) & ex\ dividend\ days \\ \ln\left(\frac{P_{d,t} f_t}{P_{d,t-1}}\right) & ex\ capitalisation\ days \end{cases}$$

where D_t is the nominal value of the expected divided and f_t is an appropriate capitalisation factor to ensure that prices represent the same proportion of the dealer's total equity value. Data used to construct D_t and f_t is also collected from SIRCA.

Corresponding to the stock exchange selected for each dealer, end-of-day index values (adjusted for dividends and capitalisation changes) for a representative market index are obtained from Yahoo Finance. Domestic benchmarks are used, rather than a single international benchmark, as the long, GFC-inclusive sample covers a period of significant volatility and structural change in global financial markets.[14] The benchmarks, which were selected for their broad coverage, are: All Ordinaries (Australia), NYSE Composite (United States), FTSE 350 (United Kingdom), SBF 250 (France), CDAX (Germany), and S&P/TSX Composite (Canada). Daily logarithmic index returns, $r_{m,t}$, are then computed using the daily market index values.

A CAPM-style model[15] is estimated using a 100-day backward-looking window for each dealer-day in the sample:

$$\left(r_{d,t} - r_{f,t}\right) = \beta_0 + \beta_1\left(r_{m,t} - r_{f,t}\right) + e_{d,t}$$

where $r_{f,t}$ is the cash rate set by the domestic central bank converted to a comparable continuously-compounded return,[16] and the coefficients β_0 and β_1 are estimated using ordinary least squares. Abnormal returns are then calculated each day as follows:

$$\hat{e}_{d,t} = \left(r_{d,t} - r_{f,t}\right) - \left(\hat{\beta}_0 + \hat{\beta}_1\left(r_{m,t} - r_{f,t}\right)\right)$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are coefficients estimated uniquely for each dealer-day. For each dealer, the bottom 10% of abnormal returns are then identified as equity-shock-days.

< INSERT TABLE 1 >

Table 1 presents the distribution of equity-shock-days by year. The total number of equity-shock-days is 2,878, which equals 10% of the total number of equity-days by definition. As expected, since financial intermediaries performed relatively worse than the market as a whole during the GFC, a disproportionally larger number of equity-shock-days occur in 2008 and 2009 (accounting for roughly 22% and 19% of all equity-days during the year). The

[14] In evaluating the performance of the capital asset pricing model (CAPM), Korajczyk and Viallet (1989) find that despite slightly outperforming a domestic benchmark index, an international benchmark index is sensitive to structural regime shifts.

[15] In unreported robustness checks, the primary results are qualitatively unchanged when considering: (a) an international market benchmark index; and (b) a different list of more popular benchmark indices.

[16] Given an overnight cash rate of $R'_{f,t}$, the equivalent continuously-compounded rate is:

$$r_{f,t} = \ln\left[\left(1 + \frac{R'_{f,t}}{365}\right)^{365}\right]$$

In any case, the difference between $R'_{f,t}$ and $r_{f,t}$ is trivial.

lowest proportion of equity-shock-days occur in the initial year 2006 (only 2.37% of all equity-days), during which financial intermediaries exhibited high performance as a result of high leverage (partly attributable to lower institutional restrictions) and lower negative shocks relative to the post-GFC period.

3.3.2 Aggregate Shock: as a secondary measure for funding scarcity, an aggregate daily dummy measure is developed. The measure considers interbank money market stress as a proxy for a shock to the funding conditions of intermediaries as a whole. Daily data on the 30-day Bank Bill Swap Rate (BBSW) and the 30-day Overnight Indexed Swap rate (OIS) are obtained from the RBA website. The top decile of all daily BBSW-OIS spreads are then identified as an aggregate funding shock. The BBSW-OIS spread is used because it is conceptually similar to the LIBOR-OIS spread, which is commonly used in the literature to proxy for funding pressures in the interbank money market (see, e.g., Frank et al. (2008)). Overall, the distribution of aggregate-shock-days is heavily concentrated during the 2007-09 GFC, much more so than the distribution of equity-shock-days.

4. EMPIRICAL MODEL

To model the effect of capital shocks on the haircut differential set by dealers, it is important to account for self-selection bias: from the final dataset of all source repos, only the fraction for which collateral is reused have an observable outcome of interest. Given that rehypothecation is intuitively a source of funding (Monnet, 2011; Singh, 2014a), it is highly likely that the decision to reuse collateral is not independent of the haircut differential variable. Hence, a two-stage Heckman model (Heckman, 1979) correcting for such bias is estimated as follows:

Stage 1:

$$\hat{Y}_{Reuse} = \alpha_0 + \alpha_1 D_{Capital\,Shock} + \alpha_2 D_{Mkt\,Stress} + \alpha_3 Inventory + \alpha_4 Reln^{*}_{P1,P2}$$
$$+\alpha_5 Amount + \alpha_6 Size + \alpha_7 Comp + \alpha_8 D_{P1=ND} + e$$

Stage 2:

$$\Delta H = \beta_0 + \beta_1 D_{Capital\,Shock} + \beta_2 D_{Mkt\,Stress} + \beta_3 \Delta R + \beta_4 Reln^*_{P3,P2} + \beta_5 Amount$$
$$+\beta_6 Size + \beta_7 Comp + \beta_8 D_{P3=ND} + \beta_9 IMR + u$$

where $\hat{Y}_{Reuse}$ is a dummy variable that indicates whether or not the collateral received in a source repo is reused and ΔH is the haircut differential applied to a reuse channel (defined as $H_1 - H_2$ to allow for an intuitive interpretation as the immediate net cash inflow at the initial leg). The primary coefficients of interest are β_1 and β_2, which aim to measure the effect of an individual dealer funding shock and an aggregate funding shock on ΔH. Table 2 provides a definition and justification for all independent variables used in the two models. Standard errors are estimated in both stages using the Newey-West procedure that is robust to heteroscedasticity and autocorrelation.

< INSERT TABLE 2 >

Stage 1 is a selection equation for which the coefficients α_i $(0 \leq i \leq 8)$ are estimated by applying a probit regression to the final dataset of all source repos. It provides an analysis of the factors affecting the likelihood that collateral received by a dealer is reused to obtain funds in a separate repo. Stage 2 is the primary substantive equation for which the coefficients β_j $(0 \leq j \leq 9)$ are estimated by applying an ordinary least squares regression. However, it only includes repos that form a reuse channel, with the correction for self-selection conducted based on the following intuition. ΔH is first assumed to be observable only when $\hat{Y}_{Reuse}$ is greater than some threshold T, and it is censored otherwise. The predicted values from the Stage 1 equation are thus used to construct an inverse Mills ratio (IMR)[17] corresponding to each observation of ΔH. IMR is then included as a control in Stage 2 for self-selection effects.

Although theoretically there is no need for exclusion restrictions due to the nonlinearity of IMR, the two stages contain a different set of variables that reflects the different factors

[17] More technically, the difference (ω) between the predicted values in Stage 1 ($E(\hat{Y}_{Reuse})$) and T is calculated for each observation of ΔH. IMR is then constructed by dividing the normal density function evaluated at ω by one minus the normal cumulative distribution evaluated at $-\omega$.

affecting dealer decision-making at each stage. The unique variables in Stage 1 include: (1) $Inventory$ as the composition of a dealer's holdings will likely affect their reuse decision but not the terms of the reuse repo; (2) $Reln^{*}_{P1,P2}$ as the prior relationship between the dealer and the collateral provider in the source repo is likely related to trust and the likelihood that the collateral provider demands segregation of their collateral; and (3) $D_{P1=ND}$ as a nondealer counterparty is likely to be in an unfavourable negotiation position. The unique variables in Stage 2 include: (1) ΔR as the dealers might compensate for a higher haircut differential (i.e., more immediate funds) with a lower repo rate differential (i.e., less funds at closing leg due to net interest); (2) $Reln^{*}_{P3,P2}$ for similar reasons to $Reln^{*}_{P1,P2}$ except that it is the prior relationship with the collateral receiver in the reuse repo that is material; and (3) $D_{P3=ND}$ for similar reasons to $D_{P1=ND}$ except that it is the reuse counterparty that is material. Overall, these exclusion restrictions allow for greater unique variation in the substantive second stage of the analysis, thereby avoiding multicollinearity problems that often confront social researchers using the Heckman model (Bushway et al., 2007).

5. RESULTS

5.1 Descriptive Analysis of Key Variables

5.1.1 Repo Rates, Haircuts, and Reuse Rates: Table 3 lists several aggregate statistics for the key repo variables across source versus reuse repos, and the summary variable RR_t. First, 3,457 of the 100,103 source repos are linked to a reuse repo to form a reuse chain. This suggests that when a dealer receives collateral in a repo, the unconditional probability that they reuse the collateral to obtain cash in a separate repo is 3.45%. This is corroborated by the average (median) weekly RR_t of 3.64% (3.09%). Although these figures are dramatically lower than the qualitative estimate of 60% proposed by Cheung et al. (2014), they are comparable but slightly lower than the 4.5% average figure reported in Fuhrer et al. (2015) for the Swiss franc repo market. The stark differences between the estimates in Cheung et al. (2014) with the repo-only estimates in this paper and Fuhrer et al. (2015) can be reconciled on three grounds: first, Cheung et al. (2014) considers all forms of Australian Treasury bond collateral reuse including securities lending, short-sales and margin requirements in addition to repos; second, the use of a matching algorithm is likely associated with a slight underestimation of collateral reuse since a fraction of unmatched repos near the start of the sample are reuse repos for out-of-sample source repos, and a fraction of repos near the end of the sample are source repos for out-of-sample reuse repos;[18] and finally, it is likely that the survey of securities dealers conducted by Cheung et al. (2014) suffers from response bias, leading to an overestimation of collateral reuse.

< INSERT TABLE 3 >

Second, there is some evidence that while the interest earnt on source repos is greater than the interest payable on reuse repos, the haircut applied on source repos is less than the haircut applied on reuse repos, which is *prima facie* inconsistent with the hypothesis that the haircut differential is used as a funding source for dealers. Given it is difficult to meaningfully compare aggregate averages and medians that do not control for time effects,[19] the following test is conducted: each week, the difference in the average (median) repo rate and haircut across source versus reuse repos is calculated; a one-sample t-test is then performed for the series of weekly differences. Table 3 documents that the weekly average (median) repo rate is significantly lower for reuse repos by 0.51% (0.42%). This figure is economically moderate in size and operates to the benefit of dealer $P2$: for a \$1m cash borrowing, the accrued interest from the reuse repo is roughly \$14 (\$12) less than the interest earnt from the source repo as the term increases by one day.[20] Table 3 also indicates that the weekly average (median) haircut is significantly higher for reuse repos by 1.29% (1.26%). This figure is large and operates to the detriment of dealer $P2$: for every \$1m in collateral value posted, the

[18] This effect is likely to be minor, however, as the dataset spans a period greater than seven years.
[19] It is interesting to note, however, that haircuts are small with an aggregate average (median) of only 0.57% (0.03%) for source repos. This indicates that for every \$1m in collateral value posted, \$994,300 (\$999,700) in cash is provided for borrowing. While these low figures likely indicate that credit risk is fairly low in the Australian repo market, they are probably also partially attributable to dealers acting as impatient short traders (who are willing to sacrifice a negative haircut to obtain a specific security).
[20] This daily net interest is calculated as $\Delta C_2 = \$1m \times (R_1 - R_2)/365 = \$1m \times \Delta R/365$. By way of comparison, the total gross interest based on the overall average source repo rate is \$113 for each day.

amount borrowed from the reuse repo counterparty is \$12,900 (\$12,600) less than the amount lent to the source repo counterparty.[21]

To investigate the progression of RR_t across market conditions, Figure 3 plots the series RR_t using a monthly time period (to reduce noise relative to a lower-frequency time period) for the aggregate sample and for each asset class separately. Prior to September 2007, the aggregate RR_t fluctuates around a 9% average. From September 2007, however, there is a clear and sudden drop in RR_t until its lowest point of under 1% in December 2007. The timing of this drop coincides with the beginning stages of the GFC, with the date 9 August 2007 (on which BNP Paribas announced its full withdrawal from three hedge funds with large exposure to mortgage securities) often cited as the starting point (Elliott, 2011). Most of this drop then persists: RR_t fluctuates around a long-run average of roughly 2.5%. Starting from early-2012, RR_t then appears to move slightly upwards towards a new long-run average. Overall, these fluctuations exhibit a similar pattern to the time series reported for the Swiss franc repo market (Fuhrer et al., 2015), apart from two key differences: first, RR_t appears to be slightly lower in Australia by several percentage points; second, the sudden drop in RR_t occurs much later in the Swiss franc repo market (mid- to late-2008, which roughly coincides with a peak point in the GFC when Lehman Brothers declared bankruptcy).

< INSERT FIGURE 3 >

From a broader perspective, the correlation between RR_t and market conditions are similar to the time-series properties of rehypothecation proposed by Singh (2014a). During normal market periods, collateral moves freely in repo markets as evidenced by the high average RR_t prior to late-2007. Concurrently, collateral velocity is intriguingly *lower* for the safest, most liquid securities (Treasury bonds), perhaps because they are used by dealers to either capture RBA funds at the lower set repo rate or to secure non-repo financial transactions external to Austraclear. Following the shock to financial intermediaries from late-2007, a larger fraction

[21] This cash borrowing difference is calculated as $\Delta C_1 = -\$1m \times (H_2 - H_1) = \$1m \times \Delta H$.

of collateral providers then demand that their collateral be segregated due to an increase in the risk that collateral cannot be returned when requested. Hence, even though $P2$ dealers have a greater need to reuse collateral to ease their funding constraint, the segregation constraint leads to an overall sharp decline in RR_t. A likely reason for the subsequent persistence of a low RR_t is higher risk aversion – and therefore a higher likelihood of collateral segregation requests – relative to pre-GFC levels: not only is collateral more scarce due to regulatory requirements (see Section 1), but also repo market participants are more concerned about counterparty risk due to continued liquidity pressures in global financial markets.

5.1.2 Haircut Differential Variable: Figure 4 plots the average monthly ΔH for the aggregate dataset and for Treasury bonds and semi-government bonds; money market securities are omitted as their small sample size makes it more difficult to discern any trends or patterns. In almost every month, ΔH is negative, in line with initial evidence from Table 3 that larger haircuts are applied to the collateral in reuse repos relative to source repos. The aggregate series is fairly stable prior to late-2011, fluctuating between 0% and -1%. However, there does appear to be a slight decline in ΔH around the GFC, which is contrary to the postulate ($Hyp2$) that haircut differentials are increased to provide an injection of immediate liquidity when other funding sources are scarce. The graph conveys a structural break in ΔH around late-2011, when the time-series drops fairly dramatically to almost -4% (i.e., the average net initial cash flow for dealer $P2$ given a \$1m loan to the source repo is almost -\$40,000): although the variability in ΔH is high following this shock, it does not return to above -1% by the end of the dataset in December 2013. Intriguingly, however, is difficult to conceptually link this period with a contemporaneous event.[22] Overall, a similar time-series pattern is observed for both Treasury bonds and semi-government bonds, although ΔH does recover back to normal levels by late-2012 for Treasury bonds.

[22] The peak of the Eurozone crisis occurred around this period. Also, the Committed Liquidity Facility (CLF) was released by the RBA in November 2011, which effectively allows banks to enter into a repo position with the RBA using collateral within a much broader class than the RBA's normal market operations. The authors are unable to find a reason why either event would lead to a substantial decline in ΔH.

< INSERT FIGURE 4 >

Table 4 provides a descriptive analysis of ΔH to more formally test $Hyp1$. Consistent with the visual evidence in Figure 4, the aggregate average haircut differential is negative, fairly large in size (indicating a -\$13,800 net initial cash flow for dealer $P2$ given a \$1m loan to the source repo) and highly statistically significant (based on a one-sample t-test). The sign and significance of ΔH is highly robust across: (1) all year-by-year aggregate subsamples; (2) all year-by-year asset type subsamples, except for Treasury bonds in 2008 and several money market years; and (3) one-sample Wilcoxon signed rank tests examining whether the median is distinguishable from zero.[23] Moreover, the insignificance of ΔH for roughly half the money market years is unlikely to be substantive but rather attributable to low statistical power as a result of a small sample size (there are only 412 reuse channels across all years for money market securities). To provide further evidence that is insensitive to outliers, Table 4 also reports the fraction of reuse channels that have a negative, zero and positive ΔH. In line with the quantitative summary measures, the fraction of reuse channels with a negative ΔH varies between 45.72% and 56.68% while the corresponding fraction with a positive ΔH varies between 10.43% and 35.85% across asset class. Overall then, it can be inferred that larger haircuts are applied to reuse repos relative to source repos, with moderate evidence for money market securities, strong evidence for Treasury bonds, and very strong evidence for semi-government bonds.

< INSERT TABLE 4 >

Taken as a whole then, Figure 4 and Table 4 provide strong evidence that ΔH is unconditionally negative, thereby rejecting $Hyp1$. Hence, rather than using reuse chains to provide a source of immediate funding, dealers obtain negative net cash flow from their reuse chains. More simple, when a dealer reuses the same collateral security, the amount of cash received from the reuse repo is less than the amount of cash lent to the source repo. This

[23] However, the median figures are smaller in magnitude than the average figures, which suggests that the distribution of ΔH is negatively skewed.

result likely reflects a multitude of factors, including: (a) dealers tend to provide cash to clients and are therefore not in a strong bargaining position in setting the terms of interdealer reuse repos; (b) dealers strategically offer a higher haircut to the reuse repo to take advantage of a cheaper interest rate, thereby increasing their net cash flow at the closing leg at the expense of a negative net cash flow at the initial leg. In a forthcoming version of this paper, these alternative explanations will be examined.

5.2 Stage I – Determinants of a Dealer's Decision to Rehypothecate

Table 5 reports the results for the initial selection analysis from the two-stage Heckman correction model across the aggregate dataset and the three asset classes. Studying the independent variables provides evidence on the factors affecting the likelihood that dealers reuse collateral, which by implication may have ramifications for our understanding of collateral velocity in global financial markets. First, while the likelihood of collateral reuse appears to be unaffected by an individual shock to the dealer receiving source collateral, it is positively affected by an aggregate funding shock to intermediaries as a whole: on the one hand, the coefficient on $D_{Capital\ Shock}$ is positive but insignificant across all probit regressions, except for marginal 10% significance for the Treasury bond asset class; on the other hand, although the coefficient on $D_{Mkt\ Stress}$ is insignificant for semi-government bonds, it is positive and significant at the 5% level in the aggregate dataset, at the 1% level in the money market and Treasury bond subsamples. Second, there is moderate evidence that higher inventory levels lead to a higher likelihood of reuse chains forming: in both the aggregate dataset and the Treasury bond subsample, the coefficient on $Inventory$ is positive and significant. This finding is interesting given that U.S. bond dealer inventories have declined sharply in recent times as a result of strict capital regulatory requirements (Avery, 2012). Third, there is strong, almost-unequivocal evidence that the likelihood of rehypothecation is positively related to the size of the repo (likely because dealers can obtain more cash from the reuse repo), and negatively related to both the relative size of dealer $P2$ (likely because controlling for the size of the repo, the immediate funds from a reuse repo are more valuable to a small dealer) and the level of competition between dealers (possibly because dealers are more likely to guarantee collateral segregation in a more competitive market).

< INSERT TABLE 5 >

There is also strong evidence that the nature of the source repo counterparty affects the probability that dealer $P2$ reuses their collateral. First, the strength of the pre-existing relationship is positive and highly statistically significant across all subsamples, apart from marginal significance for money market securities. On the one hand, at a broad level this finding corroborates the broad claim that relationships are an important economic factor in loan and other intermediary markets. On the other hand, it is opposite in direction with both a similar probit regression performed by Fuhrer (2015) in the Swiss franc repo market and with evidence of increased segregation requests by relationship collateral providers during the GFC in Duffie (2013). One possible explanation for the positive finding is that dealers are better positioned to set the terms of the repo agreement when they have a strong relationship with the counterparty, especially since there may be a high degree of trust; when the counterparty is unknown, however, the dealer must be more competitive and offer more favourable terms to the counterparty to attract market share. Second, the coefficient on $D_{P1=ND}$ is negative and highly statistically significant across all regressions, indicating that when $P1$ is a nondealer, $P2$ is less likely to rehypothecate their collateral. This result may be interpreted as reinforcing the trust versus competition explanation provided for the relationship result on the basis that competition effects are strongest when attracting order flow from nondealer clients; interdealer repos, in contrast, probably exhibit smaller spreads and follow more general practice for the reuse of collateral.

5.3 Stage II – Effect of Capital Shocks on Haircut Differentials

5.3.1 Unconditional Analysis: as a starting point for testing $Hyp2$, Table 6 provides a univariate analysis by providing summary measures for ΔH on normal days versus individual funding shock days (where $D_{Capital\ Shock} = 1$). Panel A presents the measures for each dealer separately (sorted in decreasing order by size) to provide an indication of the cross-sectional robustness of the results. On normal days, the average ΔH is negative and significant for 14 of 16 dealers, further reinforcing the rejection of $Hyp1$ in Section 5.1.2. The spread of average ΔHs is also fairly narrow. On shock days, the distribution of ΔH appears to be fairly similar to normal days, with the reduced fraction of dealers with a significant ΔH likely attributable to low sample size: as indicated by the italicised figures, nine dealers have less than 20 ΔH observations on shock days. The nominal difference in the average ΔH between shock days versus normal days (*Diff*) is then assessed to provide insight on $Hyp2$. The value of *Diff* appears to be random across dealers, with 6 of 15 dealers displaying a positive *Diff* (consistent with $Hyp2$) and the remaining 9 dealers displaying a negative *Diff*.[24] To test which of these differences are significant, a difference-of-means *t*-test is applied to the two ΔH subsamples for each dealer. Only one dealer – who has a positive *Diff* – exhibits a highly significant difference of means in ΔH across normal versus shock days, and a further two dealers – one with a positive *Diff* and the other with a negative *Diff* – exhibit a weakly significant difference of means at the 10% level.

< INSERT TABLE 6 >

Given that the dealer-by-dealer analysis provides weak evidence of an association between ΔH and funding shocks, Panel B in Table 6 lists summary statistics for the aggregate dataset. The average ΔH is -1.47% during normal days, slightly higher at -1.17% during shock days, and statistically significant for both subsamples. The difference-of-means test indicates that the two ΔH subsamples are moderately statistically distinguishable from each other (5% level). However, assessing the medians provides a slightly different picture: while the median ΔH is also statistically significant based on a one-sample Wilcoxon signed rank test for both normal days and shock days, their size is much smaller and they are not statistically distinguishable from each other based on a two-sample Wilcoxon-Mann-Whitney test. Overall then, although the unconditional summary analysis provides marginal average-based

[24] One dealer is omitted as they did not participate as party $P2$ in any reuse chains on stress days.

evidence in favour of $Hyp2$, it is important to consider this limited supportive evidence in light of other evidence: first, the median-based evidence provides no support for a difference between normal versus stress days; second, the supportive evidence is not robust across individual dealers; third, any differences have limited economic meaning since the significantly negative ΔH implies that even on shock days, most dealers realise a negative cash flow at the initial leg and therefore do not obtain any direct positive funds.

5.3.2 Primary Regression: Table 7 reports the results from the primary regression analysis for the aggregate dataset and for each asset type separately. A simple linear regression is first conducted, with the results indicating that, consistent with Section 5.3.1, an individual funding shock has no unconditional effect on ΔH: the coefficient on $D_{Capital\ Shock}$ is insignificant across all regressions; even if we ignore significance to consider the size of the coefficient, the average ΔH varies between -0.01% and -0.019% on normal days and -0.007% and -0.017% on shock days, suggesting it is not actively used to obtain positive funding for dealers. Moreover, the R^2 does not exceed 0.1% across the regressions, indicating that only a miniscule and possibly unsubstantive fraction of the variability in ΔH is explained by $D_{Capital\ Shock}$.

< INSERT TABLE 7 >

Equation (2) from the Heckman correction model is then estimated to provide a formal analysis of $Hyp2$ that controls for other variables including self-selection. On the one hand, the coefficient on the primary shock variable, $D_{Capital\ Shock}$, is insignificant and small in size across all regressions, thereby corroborating the findings from the unconditional analysis. On the other hand, the coefficient on the secondary shock variable, $D_{Mkt\ Stress}$, is positive and significant in the aggregate dataset and in the money market subsample. This indicates that when intermediaries as a whole are affected by funding illiquidity, the haircut differential tends to increase, suggesting that reuse chains are used to provide a positive capital injection. However, the evidence has limited economic implications: first, the increase is not documented for the major asset classes (Treasury bonds and semi-government bonds); second, the average increase on stress days is less than 1%, which is probably insufficient to counter the negative average ΔH on a typical non-stress day. Hence, it can be concluded that the analysis in favour of $Hyp2$ is marginal and weak.

The control variables provide useful insights into the nature of haircut differentials. First, the coefficient on ΔR is negative and highly statistically significant in all regressions – except for the money market subsample – consistent with the view that dealers face a trade-off between ΔR and ΔH. When ΔR is high, for instance, the dealer places more significance on the net interest received when negotiating the terms of the repos, and is therefore willing to sacrifice a lower initial net injection of funds (i.e., a lower ΔH). Second, there is strong evidence invariant to asset class that ΔH is positively associated with the size of the repo and with interdealer reuse repos (versus dealer-client reuse repos). The former association may be attributable to dealers being more concerned with a negative net initial cash flow when the cash lent to the source repo increases: holding ΔH constant at the average negative value, a larger source repo is associated with a larger net initial capital loss. The latter association is intuitively linked to competition effects: dealers act more competitively when bargaining with nondealers in comparison to the more standard interdealer market. Third, several control variables are sensitive to asset class. The strength of the relationship with the reuse repo counterparty, for instance, has a negatively-significant effect for Treasury bond collateral and a positively-significant, large-sized effect for semi-government bond collateral. This result intriguingly suggests that dealers are more readily able to exploit their relationships and potentially obtain a positive haircut differential when the collateral reused is within the less-liquid semi-government bond asset class.

5.3.3 Robustness Checks and Overall Assessment: after conducting multiple robustness checks, the results for the individual shock effect and the aggregate shock effect remain broadly consistent. This section outlines the sensitivity of the coefficient on the primary variable, $D_{Capital\ Shock}$, to several of these checks. First, stage 2 of the Heckman correction model is re-estimated to incorporate fixed effects methods that allow for a different average ΔH for cross-section or time-series units. As shown in Table 8, the insignificance of ΔH is invariant to the inclusion of daily fixed effects, dealer fixed effects, and both daily and dealer fixed effects: across these 12 further regressions, there is only marginal evidence that $D_{Capital\ Shock}$ is positive and significant when including daily fixed effects for the Treasury bond sample.

< INSERT TABLE 8 >

Second, since it is possible that a dealers ability to control ΔH during a shock is related to other market variables, a simple robustness check is conducted to account for interactions. Table 9 presents the results from re-estimating the two-stage Heckman correction model for the bottom 50% and the top 50% of values for several control variables. The primary coefficient on $D_{Capital\ Shock}$ is positive and significant for several subsamples, including when the repo size is small, when the reuse repo counterparty is a nondealer, and when the dealer is foreign. Perhaps most interestingly, the coefficient is positive and significant when ΔR is low for the Treasury bond asset class. This is consistent with the proposition that in order to increase ΔH after a funding shock, a dealer must compensate the reuse repo party by setting a lower ΔR. Despite the existence of some evidence in line with $Hyp2$ in Table 9, however, the coefficients are small: for every subsample, if $D_{Capital\ Shock}$ is set to zero and all the control variables are set to their average value, the average ΔH given the estimated coefficients is either negative or economically indistinguishable from zero. Third, in a forthcoming version of this paper, the analysis will be re-performed for different definitions of the individual shock variable.

< INSERT TABLE 9 >

Taken as a whole, the results provide only marginal evidence that individual shocks and aggregate shocks lead to an increase in haircut differentials for certain subpopulations.

Moreover, this limited support of $Hyp2$ can only be reasonably interpreted in light of an important proviso: the discernible increases in ΔH after funding shocks are not sufficiently large to lead to a positive ΔH, implying that the average net initial cash flow from the reuse chain remains negative. Especially given strong evidence that ΔH is negative in both normal and shock periods, our results are consistent with an alternative conception of ΔH: given competition effects and the role of two-way bargaining, dealers are unable to actively set and use ΔH as a positive funding channel in repo markets.

6. CONCLUSION

Motivated by our limited understanding of the microeconomics of collateral use, this paper aims to provide the first empirical study of rehypothecation as a direct funding mechanism for dealers. After conducting a supplementary descriptive analysis on rehypothecation activity, the paper uses unique data from the Australian repo market to test two primary hypotheses that stem from the theoretical models of Eren (2014) and Infante (2014). First, that the haircut margin (denoted as the haircut differential, ΔH) between the initial, source repo and the subsequent, reuse repo is positive, consistent with an immediate positive cash flow for dealers that have a strong preference for current cash relative to future cash. Second, that after a shock to the funding liquidity of dealers, the haircut differential is increased to provide a larger initial capital injection, thereby easing funding conditions.

Taken as a whole, the results strongly reject the direct funding mechanism hypotheses. In terms of the first hypothesis, the evidence that haircut differentials are *negative* is fairly compelling. A monthly time series graph first indicated that the average haircut differential is almost always negative for the aggregate dataset as well as for Treasury bonds and semi-government bonds separately. A more formal test then showed that the aggregate haircut differential is negative and statistically significant in every year; this result is also fairly robust when examining each asset type in isolation. Further, the median haircut differential is negative and statistically significant based on a Wilcoxon signed rank test for the aggregate dataset and each asset type. Finally, the proportion of reuse chains with a negative haircut differential is slightly over 50% while the corresponding proportion with a positive haircut differential is under 18%. Overall then, it can be concluded that dealers tend to receive a negative cash flow at the initial leg of reuse chains.

In terms of the second hypothesis, a primary individual-level shock and a secondary market-level shock are studied. Unconditionally, the average haircut differential on normal days is statistically greater than the average haircut differential on shock days, consistent with Eren's (2014) prediction. However, this result is not robust across dealers and there is no evidence of a difference in the medians. When a two-stage Heckman model is estimated to control for self-selection bias and other factors, there is no evidence that an individual-level shock leads to an increase in the haircut differential. There is evidence that a market-level shock is associated with a higher haircut differential, although the evidence is insignificant for Treasury bonds and semi-government bonds. Also, robustness checks proved that although there might be some interesting interactions, the results are broadly insensitive to methodological changes. Perhaps most importantly, the haircut differential is still negative on shock days, so marginal evidence of a higher haircut differential is economically insignificant since dealers are still not using rehypothecation to receive a direct, immediate cash flow.

At a broad level, the inconsistency between these results and the direct funding mechanism hypothesis can be traced to a problematic assumption in Eren (2014): that dealers hold all the bargaining power and set take-it-or-leave-it offers. In practice, it is probable that after receiving specific collateral from the source repo, the dealer acts with a greater sense of urgency to fund the cash lent by rehypothecating the collateral. The counterparty in the reuse repo is therefore more likely to be a dealer and is in an advantageous bargaining position. Hence, the dealer is effectively forced to accept a lower cash inflow. In a related light, the notion that dealers with idle collateral are in an inferior position and may be exploited is corroborated by the initial descriptive analysis of rehypothecation: although dealers have a greater demand to rehypothecate during crisis periods, the reuse rate declines dramatically at the start of the GFC, reflecting increased demand by source party repos for collateral segregation. Looking forward, the results in this paper provide the motivation for research towards a new alternative theory of rehypothecation that accounts for these effects.

A key limitation of the study – which also poses another area for future research – is that haircut differentials are studied in isolation to repo rate differentials. Although the repo rate differential is included as a control, ideally a simultaneous system of two equations – one for explaining the haircut differential and another for explaining the repo rate differential – should be proposed and estimated to more accurately reflect the fact that dealers jointly set these two repo terms. This paper did not attempt such an analysis due to identification issues, which would result in simultaneity bias. Nonetheless, despite the potential for this methodological improvement, the fundamental result that haircut differentials are negative remains highly persuasive and an important contribution for our understanding of the intricate mechanics of collateral reuse.

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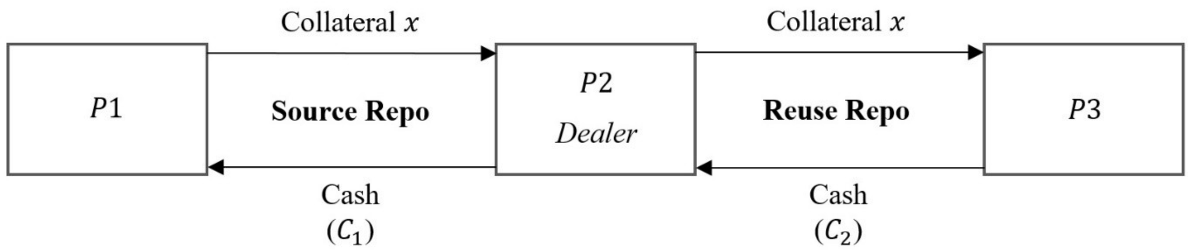
TABLES AND FIGURES

Figure 1

Structure of a Reuse Chain

This image depicts the structure of a reuse chain, which is composed of a source repo and a subsequent reuse repo. In the initial leg, the dealer $P2$ receives collateral x from $P1$ in return for lending cash C_1. The collateral x is then reused to secure a separate repo with $P3$, who lends the dealer $P2$ cash C_2. At the closing leg of the two repos, $P2$ first collects the collateral x from $P3$ and repays the principal cash C_2 plus interest at the rate R_2. The dealer $P2$ then returns the collateral x to the original owner $P1$ and receives the principal cash C_1 plus interest at the rate R_1. In the analysis conducted, $P1$ and $P3$ can be either a dealer or a nondealer, but not the RBA.

(a) Initial Leg



(b) Closing Leg

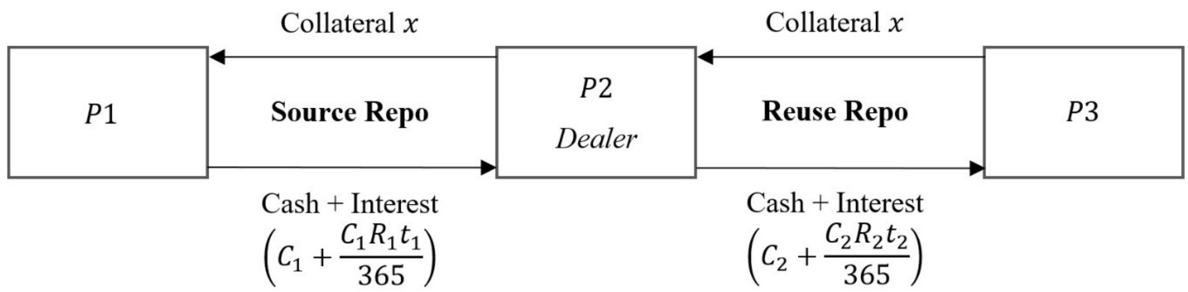


Figure 2

Flowchart of Data Filters

This flowchart provides an explanation of the filters applied to modify the raw Austraclear dataset into the final dataset that is used for analysis. The chart indicates the sample size of the initial dataset, a step-by-step explanation of each filter, and the sample size of the final dataset.

Initial Dataset

337,770 repos

Filter 1: include only money market, TBs and SGBs

Filter 2: exclude RBA repos (*only major filter*: deletes roughly 50%)

Filter 3: exclude intraday repos and repos with a term greater than 14 days

Filter 4: exclude first 50 trade days

Filter 5: include only repos with a dealer as the collateral receiver

Filter 6: exclude repos for which the value of collateral (V_1) cannot be accurately calculated as the benchmark group-day has less than five cash trades (see Section 3.2.1)

Final Dataset
100,103 repos

Table 1

Distribution of Equity-Shock-Days by Year

This table presents the distribution of equity-shock-days across years. *Shock Days* refers to the total number of equity-shock-days in a given year across all dealers. *Total Days* refers to the total number of dealer-days in a given year (i.e., not just the number of days). *% Shock Days* is calculated by as *Shock Days* ÷ *Total Days*, and should be 10% in each year if there is an equal proportion (weighted by the fraction of *Total Days*) of equity-shock-days in each year.

Year	Shock Days	Total Days	% Shock Days
2006	32	1348	2.37%
2007	221	4166	5.30%
2008	891	3961	22.49%
2009	761	4044	18.82%
2010	294	3920	7.50%
2011	324	3785	8.56%
2012	193	3779	5.11%
2013	162	3778	4.29%
Total	2,878	28,781	10%

Table 2

List of Variables in Heckman Correction Model

This table lists the dependent and independent variables used in the Heckman correction model:

Stage 1:

$$\hat{Y}_{Reuse} = \alpha_0 + \alpha_1 D_{Capital\ Shock} + \alpha_2 D_{Mkt\ Stress} + \alpha_3 Inventory + \alpha_4 Reln^*_{P1,P2} + \alpha_5 Amount$$
$$+\alpha_6 Size + \alpha_7 Comp + \alpha_8 D_{P1=ND} + e$$

Stage 2:

$$\Delta H = \beta_0 + \beta_1 D_{Capital\ Shock} + \beta_2 D_{Mkt\ Stress} + \beta_3 \Delta R + \beta_4 Reln^*_{P3,P2} + \beta_5 Amount + \beta_6 Size$$
$$+\beta_7 Comp + \beta_8 D_{P3=ND} + \beta_9 IMR + u$$

The full definition of each variable (including how it is measured) is provided.

Variable	Definition and Justification for Inclusion
$\hat{Y}_{Reuse}$	Dummy variable that indicates whether or not the collateral received by the dealer in a source repo is subsequently reused. It is a selection variable that models the dealer's decision to rehypothecate.
ΔH	The difference in haircut applied to the reuse repo versus the source repo. This variable is only observed when $\hat{Y}_{Reuse}$ is greater than some threshold T, and it is censored if $\hat{Y}_{Reuse} \leq T$. It is constructed as $H_1 - H_2$, rather than $H_2 - H_1$, to allow for the variable to be more intuitively interpreted as the net cash inflow at the initial leg from dealer $P2$s perspective. It is conjectured to serve as a funding mechanism for dealers (see Infante (2014) and Eren (2014)).
$D_{Capital\ Shock}$	Dummy variable that takes the value of 1 on trade days when the close-to-close risk-adjusted equity return of dealer $P2$ is within the bottom decile of all $P2$'s trade days. Risk-adjustment is achieved by applying a simple daily returns model with a market benchmark return factor. A shock to equity capital serves as a simple

	proxy for an *individual* shock to dealer $P2$s funding liquidity, which Eren (2014) shows leads to an increase in ΔH.
$D_{Mkt\ Stress}$	Dummy variable that takes the value of one on trade days when the spread between the 30-day Bank Bill Swap Rate (BBSW) and the 30-day Overnight Indexed Swap rate (OIS) is within the top decile of all trade days. BBSW and OIS rates are obtained from the RBA website. The BBSW-OIS spread is conceptually similar to the LIBOR-OIS spread commonly used in the literature as a proxy for funding pressures in the interbank money market (see, e.g., Frank et al. (2008)). It serves as a proxy for an *aggregate* shock to the funding liquidity of dealers, which Eren (2014) shows leads to an increase in ΔH.
$Inventory$	The logarithm of the total face value of the collateral security that is held in dealer $P2$'s inventory at the close of the previous trade day. A logarithmic transformation is applied for its variance-stabilising features: the raw variable is large in size and has an extremely high variance. As the holdings of the collateral security held by dealer $P2$ increases, the risk associated with reusing the collateral decreases, and the dealer is therefore more likely to reuse it in a repo. This variable can also be justified by viewing short-sales as an alternative to reuse repos: the fraction of repos that are used by dealer $P2$ for short-selling the collateral security (thereby not forming a reuse chain) is higher when they do not hold a long-position by having a positive inventory.
ΔR	The difference in the repo rate applied to the reuse repo versus the source repo. It is constructed as $R_1 - R_2$, rather than $R_2 - R_1$, to allow for the variable to be more intuitively interpreted as the net interest inflow at the closing leg from dealer $P2$s perspective. Intuitively, when dealer $P2$ sets a higher haircut differential to obtain immediate liquidity at the initial leg, they might need to compensate the reuse repo party ($P3$) by paying them greater interest at the closing leg. The notion of a trade-off between ΔR and ΔH is modelled by Eren (2014).
$Size$	Size index measured as dealer $P2$s market share, where the market share is the total value of cash borrowings in repos that $P2$ participates in as a proportion of the total value of cash borrowings across all dealer repos. A backward-window of the previous 50 trade days is used. The set of repos considered is all non-RBA repos that at least one dealer participates in with either a Treasury bond, a semi-government bond or a money market security as collateral. Larger dealers are more likely to have greater resources and information (due to more active involvement in the opaque repo market), which likely leads to greater bargaining power in setting repo terms including the capacity to more freely reuse collateral (less segregation requests) and set a higher ΔH.
$Comp$	Herfindahl index that captures overall dealer competitiveness. It is constructed by taking the sum of the squares of each individual dealer's market share (i.e., the $Size$ variable). A backward-window of the previous 50 trade days is used. The set of repos considered is all non-RBA repos that at least one dealer participates in with either a Treasury bond, a semi-government bond or a money market security as collateral. When intermediaries are more competitive, collateral reuse is likely to be lower (as collateral segregation might otherwise be readily obtainable elsewhere), and it is more difficult to exploit their position and set a favourable ΔH (shown theoretically by Eren (2014)).
$D_{P1=ND}$	Dummy variable that indicates whether $P1$ is a nondealer, making the source repo a dealer-client transaction (as opposed to an interdealer transaction). Due to their limited resources and information disadvantage (due to lower trade frequency), nondealer clients may be in an unfavourable bargaining position, leading to better repo terms for the dealer including the ability to reuse collateral.
$D_{P3=ND}$	Dummy variable that indicates whether $P3$ is a nondealer, making the reuse repo a dealer-client transaction (as opposed to an interdealer transaction). Similar reasoning for inclusion as $D_{P1=ND}$.
$Reln^{*}_{P1,P2}$	Relationship strength measure for $(P1, P2)$ that controls for the expected proportion of repos going through $P2$. It is defined as $Reln_{P1,P2} - Active_{P2}$, where $Reln_{P1,P2}$ is the proportion of all repos that $P2$ participates in during the previous 50 trading days that include $P1$ as a counterparty, and $Active_{P2}$ is the

	proportion of all repos during the same 50-day window that $P2$ participates in. The set of repos considered is all non-RBA repos that at least one dealer participates in with either a Treasury bond, a semi-government bond or a money market security as collateral. There is a well-established relationship banking literature in the context of unsecured loans (see, e.g., Boot (2000) or Elyasiani and Goldberg (2004) for a review), and Fuhrer (2015) shows that relationship strength is related to the likelihood that collateral is reused.
$Reln^{*}_{P3,P2}$	Relationship strength measure for $(P3, P2)$ that controls for the expected proportion of trades going through $P2$. It is defined with a similar structure, and has a similar justification, to $Reln^{*}_{P1,P2}$.
IMR	Inverse mills ratio estimated for each observation by dividing the normal density function at $-(T - \hat{Y}_{Reuse})$ by one minus the normal cumulative distribution estimated at $-(T - \hat{Y}_{Reuse})$.

Table 3

Descriptive Analysis of Austraclear Repo Data

This table reports aggregate statistics for trade activity in the Austraclear dataset used for analysis (1 September 2006 to 31 December 2013). The results are presented separately for source repos ("Source") and reuse repos ("Reuse"), with standard summary measures (average, median, and standard deviation) being reported. In terms of the variables, *N* refers to the number of observations in the dataset, *Repo rate* refers to the repo rate underlying a repo transaction, and *Haircut* refers to the haircut underlying a repo transaction. For *Repo rate* and *Haircut*, the "Diff" column conducts the following test for each of the three summary statistics: at a weekly frequency, the difference between the statistic for reuse repos and source repos is taken ($\Delta Stat$); a one-sample *t*-test examining whether the weekly series $\Delta Stat$ is distinguishable from zero is then conducted, with the average weekly $\Delta Stat$ reported below. The final variable, *Reuse rate*, is a relative measure of re-use activity in the repo market, and is defined as the ratio of the market value of collateral used to secure reuse repos to the overall market value of collateral securing repos (i.e., both reuse and source repos); it is measured at a weekly frequency. For the $\Delta Stat$ one-sample *t*-test, ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

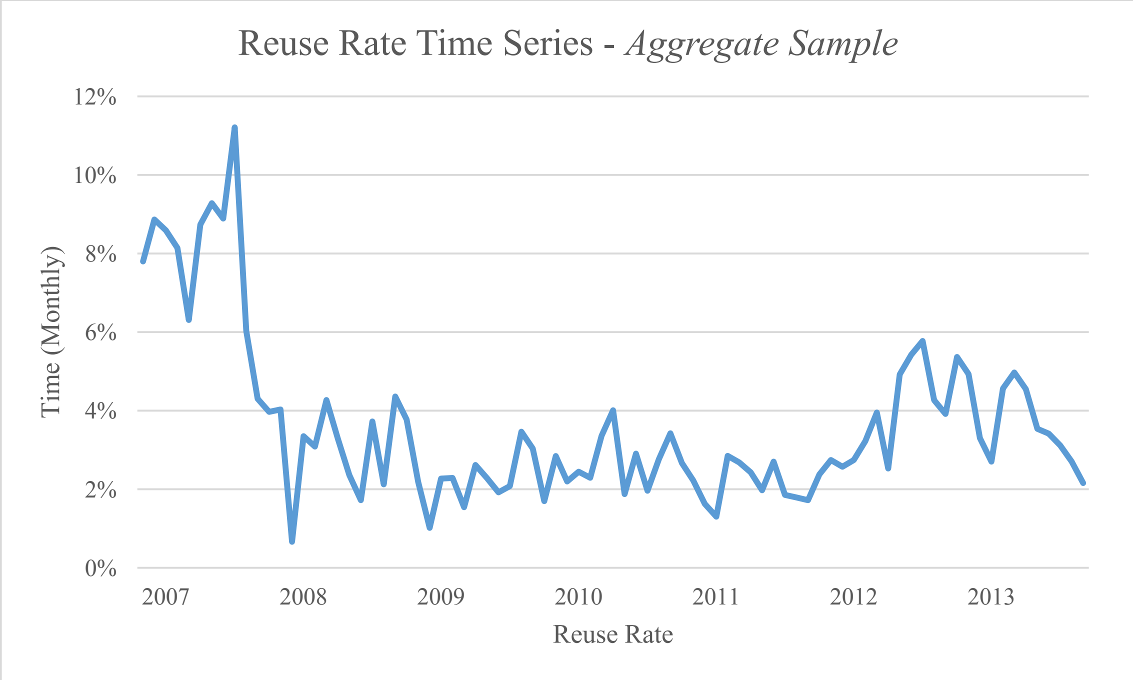
	Source	Reuse	Diff
N	100,103	3,457	
	(96.66%)	(3.34%)	
Repo rate			
- Average	4.11%	3.73%	-0.51%***
- Median	4.20%	3.90%	-0.42%***
- Stdev	1.50%	2.25%	0.27%
Haircut			

- Average	0.57%	1.86%	1.29%***
- Median	0.03%	0.45%	1.26%***
- Stdev	2.37%	3.87%	0.71%***
Reuse rate			
- Average			3.64%
- Median			3.09%
- Stdev			3.53%

Figure 3

Time-Series Graph of Reuse Rate

This graph presents the time-series variable *Reuse Rate*. *Reuse Rate* is a relative measure of re-use activity in the repo market, and is defined as the ratio of the market value of collateral used to secure reuse repos to the overall market value of collateral securing repos (i.e., both reuse and source repos). For clarity, it is measured at a monthly frequency. The graphs are presented for both the aggregate dataset and for each asset class separately.



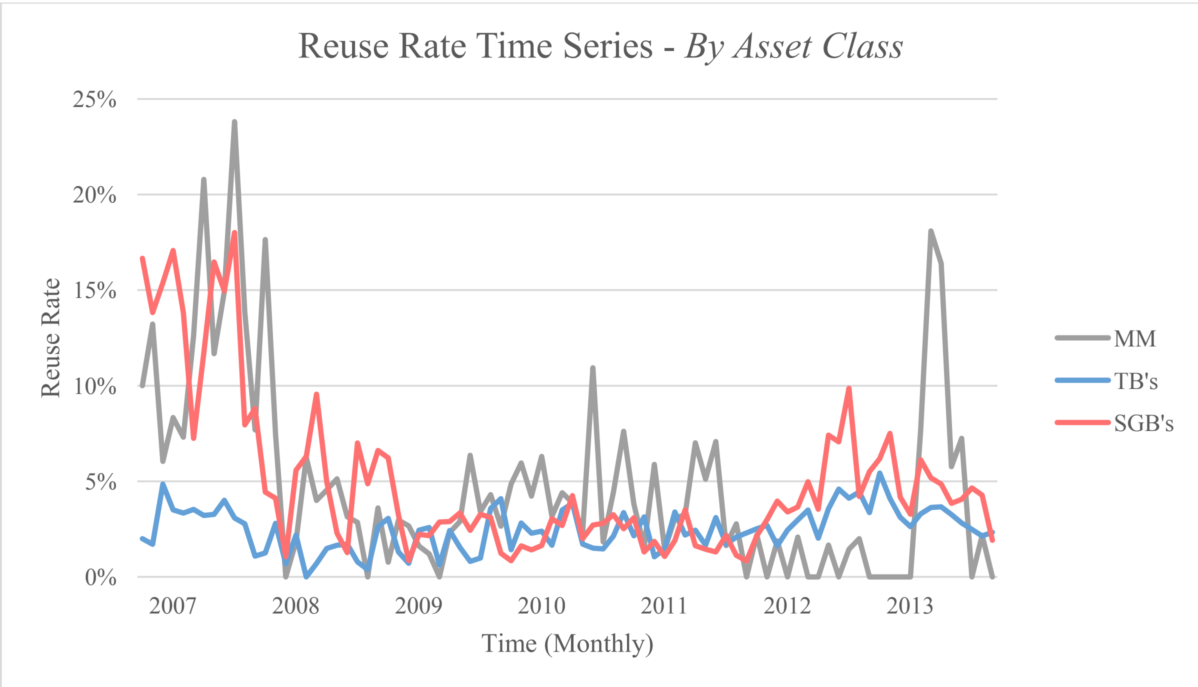
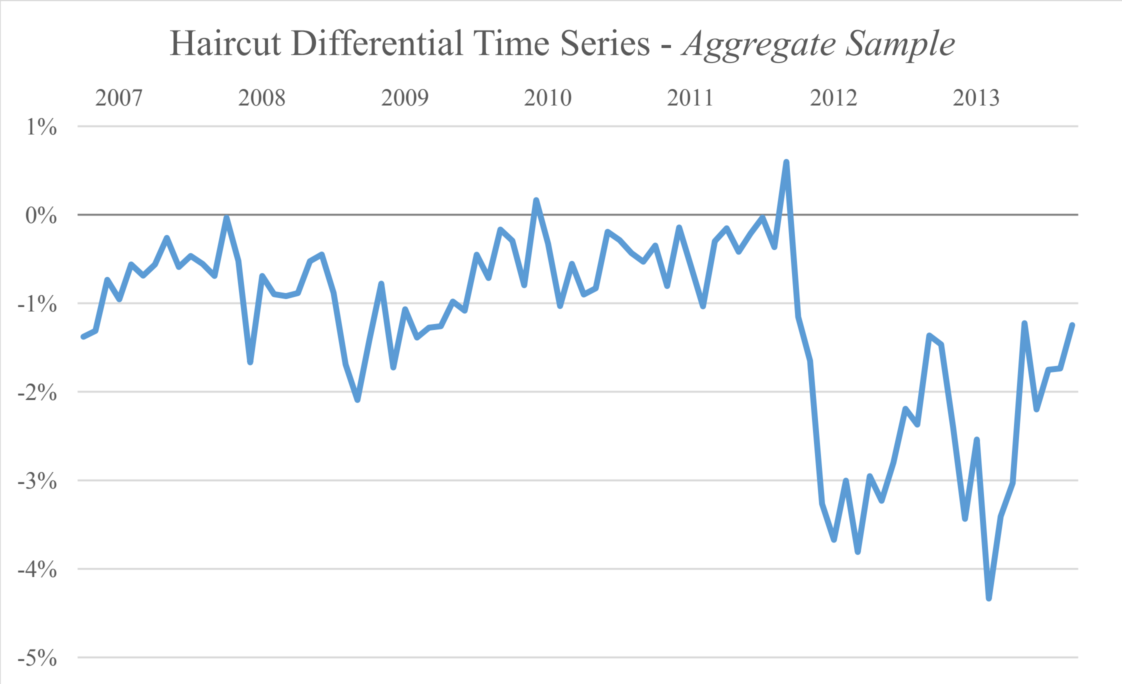


Figure 4

Time-Series Graph of Haircut Differential

This graph presents a summarised time-series haircut differential variable (ΔH). ΔH is the primary variable in this study, and is defined for each reuse chain as the haircut applied to the source repo minus the haircut applied to the reuse repo. For clarity, the monthly observations plotted represent the average ΔH across all reuse chains in each month. The graphs are presented for both the aggregate sample and for each asset class separately (excluding money market securities due to small sample size issues).



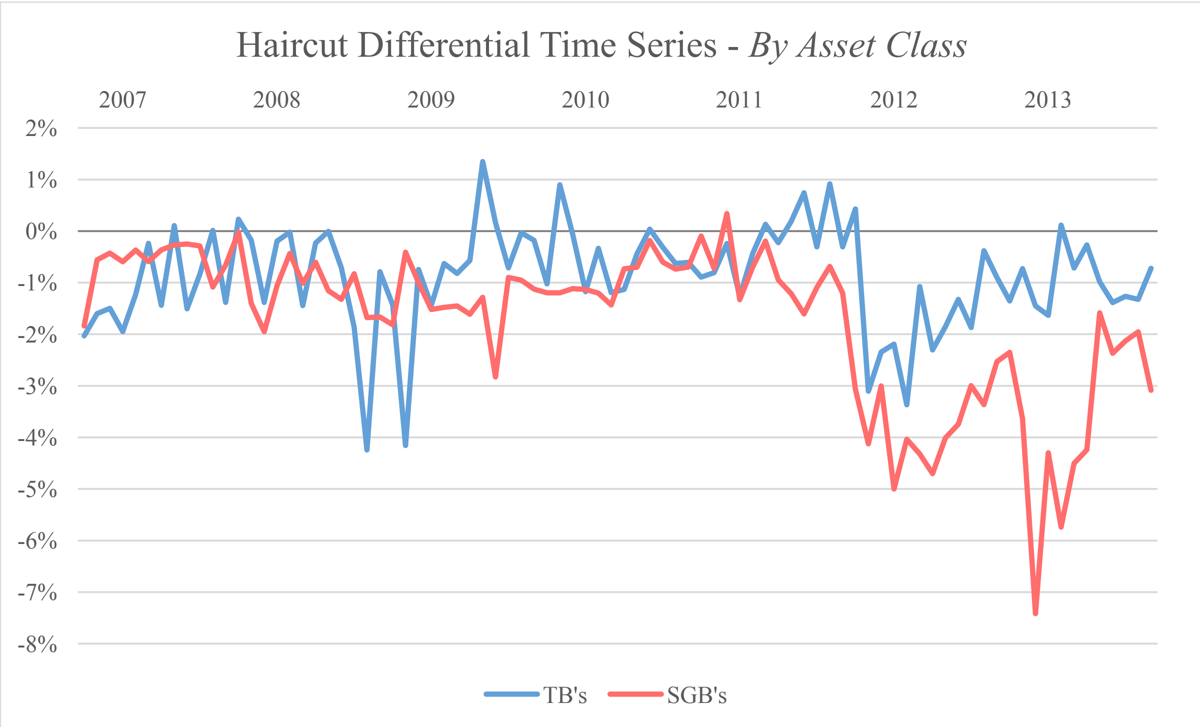


Table 4

Descriptive Analysis of Haircut Differential Variable

This table reports summary statistics for haircut differentials (ΔH) in the repo market. ΔH is the primary variable in this study, and is defined for each reuse chain as the haircut applied to the source repo minus the haircut applied to the reuse repo. Panel A presents the average ΔH in each year. Panel B presents the number of observations (*Obs*), average (*Mean*), median (*Median*), and standard deviation (*Stdev*) for ΔH across the full time period. For Panel A and for the *Mean* row in Panel B, a one-sample *t*-test is applied to determine whether the series of repo-by-repo ΔH's are statistically distinguishable from zero. For the *Median* row in Panel B, a one-sample Wilcoxon signed rank test is applied to determine whether the series of repo-by-repo ΔH's are statistically distinguishable from zero. The results are presented for both the aggregate dataset and for each asset class separately. Summary figures are italicised if they represent a subsample of less than 20 observations. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Variable of Interest: ΔH			
	All	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Panel A: Year-by-Year				
2006 (partial)	-1.02%***	-2.49%*	-1.52%***	-0.51%***
2007	-0.53%***	-0.50%***	-0.81%***	-0.44%***
2008	-0.83%***	-0.83%***	-0.43%	-0.94%***
2009	-1.15%***	-0.39%**	-1.01%***	-1.44%***
2010	-0.48%***	-0.00%	-0.44%***	-0.84%***
2011	-0.42%***	-0.03%	-0.41%***	-0.58%***
2012	-2.59%***	*-1.54%*	-1.57%***	-3.75%***
2013	-2.46%***	-8.89%***	-0.86%***	-3.57%***
Panel B: Aggregate				
Obs	3,457	412	1,483	1,562
Mean	-1.38%***	-1.39%***	-0.85%***	-1.88%***
Median	-0.05%***	-0.01%***	-0.09%***	-0.63%***
Stdev	3.35%	3.16%	3.16%	3.50%
% $\Delta H < 0$	50.92%	49.02%	45.72%	56.68%
% $\Delta H = 0$	31.85%	15.13%	35.31%	32.89%
% $\Delta H > 0$	17.23%	35.85%	18.96%	10.43%

Table 5

Stage I Heckman Correction Model – Qualitative Probit Analysis

This table presents a qualitative probit analysis of the effect of various variables on the likelihood that collateral received by a dealer is re-used to undertake a repo position in a separate repo. The analysis is conducted for both the aggregate dataset and for each asset type separately. Since the aim of this first-stage regression is to control for self-selection bias in the primary second-stage model (by allowing an inverse mills ratio to be constructed), there is no independent variable of interest. In terms of the control variables, $D_{Capital\ Shock}$ refers to days when the dealer ($P2$) suffered an abnormal negative return in the equity market on the previous trade day, $Inventory$ refers to the logarithm of the market value of the collateral security held by dealer ($P2$) at the close of the previous trade day, $Reln^{*}_{P1,P2}$ refers to the strength of the relationship between the dealer ($P2$) and the collateral provider ($P1$) in the source repo, $D_{Mkt\ Stress}$ is an indicator variable that takes the value of one on market stress days, $Amount$ refers to the logarithm of the amount borrowed in the source repo, $Size$ refers to the relative size of the dealer ($P2$) in the repo market, $Comp$ refers to the competition level amongst dealers in the repo market, and $D_{P1=ND}$ is an indicator variable that takes the value of one if the collateral provider ($P1$) in the source repo is a non-dealer. For each independent variable, the estimated coefficient and test statistic (in brackets) is reported. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. The final two rows report the likelihood ratio (λ^2) testing for significance of the model as a whole and the number of observations (Obs). ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: $P(Rehyp = 1)$			
	All	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Intercept	-0.765***	-2.843***	-2.646***	-1.6864***
	(38.74)	(44.03)	(253.44)	(76.07)
$D_{Capital\ Shock}$	0.014	0.010	0.085*	0.0497
	(0.24)	(0.01)	(3.01)	(0.99)
$Inventory$	0.0023**	0.0012	0.810***	0.00
	(5.02)	(1.30)	(18.48)	(0.10)
$Reln^{*}_{P1,P2}$	1.179***	0.314*	0.685***	1.2747***
	(719.23)	(2.71)	(122.09)	(337.93)
$D_{Mkt\ Stress}$	0.071**	0.371***	0.201***	-0.0018
	(5.21)	(17.10)	(12.49)	(0.00)
$Amount$	0.045***	0.142***	0.062***	0.0684***
	(110.88)	(46.06)	(75.29)	(66.40)
$Size$	-2.063***	0.289	-2.517***	-1.7713***
	(251.06)	(2.11)	(241.56)	(103.36)
$Comp$	-3.943***	-5.391***	-0.754**	-3.0145***
	(42.18)	(49.81)	(4.17)	(49.63)
$D_{P1=ND}$	-0.497***	-0.323***	-0.337***	-0.7924***
	(1106.84)	(34.31)	(200.55)	(827.74)
λ^2	3525.40***	195.51***	1079.68***	1965.41***
Obs	100,103	8,016	56,157	35,930

Table 6

Descriptive Analysis of Haircut Differential Variable – Normal versus Shock Days

This table reports summary statistics for haircut differentials (ΔH) in the repo market across normal versus equity-shock days. ΔH is defined for each reuse chain as the haircut applied to the source repo minus the haircut applied to the reuse repo. Panel A presents the average ΔH for each dealer under "Normal Days" and "Shock Days", sorted in descending order by size. "Diff" provides the difference between the shock average ΔH and normal average ΔH for each dealer. Panel B presents the average (*Mean*), median (*Median*), and standard deviation (*Stdev*) for ΔH under "Normal Days" and "Shock Days", with "Diff" defined similarly to Panel A. For Panel A and for the *Mean* row in Panel B:

a. A one-sample t-test is applied under "Normal Days" and "Shock Days" to determine whether the series of repo-by-repo ΔH's are statistically distinguishable from zero.
b. A difference-of-means t-test is applied under "Diff" to determine whether the "Normal Days" and "Shock Days" ΔH samples are statistically distinguishable from each other.

For the *Median* row in Panel B:

a. A one-sample Wilcoxon signed rank test is applied under "Normal Days" and "Shock Days" to determine whether the series of repo-by-repo ΔH's are statistically distinguishable from zero.
b. A two-sample Wilcoxon-Mann-Whitney test is applied under "Diff" to determine whether the "Normal Days" and "Shock Days" ΔH samples are statistically distinguishable from each other.

Summary figures are italicised if they represent a subsample of less than 20 observations. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Variable of Interest: ΔH		
	Normal Days	Shock Days	Diff
Panel A: Dealer (by size)			
1	-2.40%***	-1.29%***	1.11%***
2	-1.27%***	-1.48%***	-0.21%
3	-1.45%***	-1.51%***	-0.06%
4	-0.86%***	-1.17%***	-0.30%
5	-0.67%***	-0.83%***	-0.16%
6	-0.43%***	*0.08%*	0.50%
7	-0.29%***	*-0.05%*	0.25%
8	-1.71%***	-1.98%***	-0.27%
9	-0.01%	-0.81%**	-0.80%*
10	-1.20%***	*-1.37%***	-0.17%
11	-0.91%***	*0.14%*	1.04%*
12	-0.43%***	*-1.11%*	-0.68%
13	-0.61%***	*-0.34%*	0.28%
14	-0.52%**	*-1.09%*	-0.57%
15	-1.95%***	*-1.36%**	0.59%
16	*-0.27%*	-	-
Panel B: Aggregate			
Mean	-1.47%***	-1.17%***	0.30%**
Median	-0.06%***	-0.00%***	0.06%
Stdev	3.50%	2.32%	

Table 7

Stage II Heckman Correction Model – Haircut Differential Analysis

This table presents a regression analysis of the effect of an exogenous dealer capital shock on haircut differentials (ΔH) in the repo market. The analysis is conducted for both the aggregate dataset and for each asset type separately. A preliminary regression without any control variables is first estimated under (6a), (6d), (6f), and (6g). A primary regression representing the second stage of the Heckman correction model is then presented in the other columns; in these regressions, the inverse mills ratio (IMR) estimated using the corresponding probit function in Table 4 is included as a control for self-selection bias. The dependent variable (ΔH) is defined for each reuse chain as the haircut applied to the source repo minus the haircut applied to the reuse repo. The key variable of interest is $D_{Capital\ Shock}$, defined as days when the dealer ($P2$) suffered an abnormal negative return in the equity market on the previous trade day. In terms of the control variables, ΔR refers to the repo rate differential between the reuse repo and the source repo, $Reln^{*}_{P3,P2}$ refers to the strength of the relationship between the dealer ($P2$) and the collateral receiver ($P3$) in the reuse repo, $D_{Mkt\ Stress}$ is an indicator variable that takes the value of one on market stress days, $Amount$ refers to the logarithm of the average amount borrowed in the source repo and reuse repo, $Size$ refers to the relative size of the dealer ($P2$) in the repo market, $Comp$ refers to the competition level amongst dealers in the repo market, and $D_{P3=ND}$ is an indicator variable that takes the value of one if the collateral receiver ($P3$) in the reuse repo is a non-dealer. For each independent variable, the estimated coefficient and test statistic (in brackets) is reported. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: ΔH							
	All		Money Mkt		Treasury Bonds		Semi-Gov Bonds	
	(6a)	(6b)	(6d)	(6e)	(6f)	(6f)	(6g)	(6i)
Intercept	-0.015***	-0.041***	-0.015***	0.021***	-0.010***	-0.118***	-0.019***	-0.078***
	(-23.56)	(-4.40)	(-8.47)	(4.28)	(-10.31)	(-7.18)	(-20.63)	(-4.90)
$D_{Capital\ Shock}$	0.002	0.0021	-0.001	0.0008	0.003	0.0007	0.002	0.0074
	(0.84)	(0.61)	(-0.19)	(0.40)	(0.92)	(0.16)	(0.97)	(1.40)
ΔR		-0.668***		-0.0003		-0.675***		-1.012***
		(-22.48)		(-0.02)		(-14.95)		(-16.36)
$Reln^{*}_{P3,P2}$		0.015***		0.0003		-0.015**		0.042***
		(3.16)		(0.19)		(-2.55)		(4.57)
$D_{Mkt\ Stress}$		0.0094***		0.0065***		0.0004		0.0017
		(2.89)		(2.88)		(0.06)		(0.25)
$Amount$		0.0032***		0.0010*		0.0025***		0.0045***
		(7.10)		(1.85)		(4.14)		(6.70)
$Size$		0.017**		-0.020***		-0.112***		0.057***
		(2.36)		(-4.50)		(-7.33)		(4.21)
$Comp$		-0.077***		0.084***		-0.041		-0.031

		(-3.71)		(4.56)		(-1.22)		(-0.79)
$D_{P3=ND}$		-0.0060***		-0.0001		-0.0042**		-0.0094***
		(-4.29)		(-0.18)		(-2.12)		(-3.39)
IMR		x		x		x		x
F-value	0.70	60.55***	0.04	21.75***	0.85	19.80***	0.95	42.37***
$\bar{R}^2$	0.000	0.043	0.000	0.028	0.001	0.061	0.000	0.039
Obs	3,457	2,322	412	297	1,483	1,064	1,562	961

Table 8

Robustness of Stage II Heckman Correction Model to Panel Data Techniques

This table presents the results from estimating the primary regression model (as in Table 7) using various panel data techniques. This robustness check is conducted for both the aggregate dataset and for each asset type separately. The figures represent the coefficient on the key variable of interest, $D_{Capital\ Shock}$, for each technique. *Primary model* is the base primary model in Table 7 without any fixed effects. *Dealer FEs* is the base primary model in Table 7 with the addition of dealer ($P2$) fixed effects. *Day and Dealer FEs* is the base primary model in Table 7 with the addition of both daily and dealer ($P2$) fixed effects. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: ΔH			
	Coefficient on $D_{Capital\ Shock}$			
	All	Money Mkt	Treasury Bonds	Semi-Gov Bonds
Primary model	0.0021	0.0008	0.0007	0.0074
Day FEs	0.0044	-0.0075	0.0052*	-0.0059
Dealer FEs	0.0020	0.0048	0.0030	0.0069
Day and Dealer FEs	0.0015	-0.0024	0.0066	-0.0032

Table 9

Robustness of Stage II Heckman Correction Model to Interactions

This table presents the results from estimating the primary regression model (as in Table 7) for various subsamples to control for interactions. This robustness check is conducted for each asset type separately. The figures represent the coefficient on the key variable of interest, $D_{Capital\ Shock}$, for each subsample. For each quantitative control variable, the primary regression model is estimated separately for the largest 50% of values (under "Top 50%") and for the smallest 50% of values (under "Bottom 50%"). For the two indicator control variables ($D_{P3=ND}$ and $D_{Foreign}$), the primary regression model is estimated separately for observations with a value of zero (under "Top 50%") and for observations with a value of one (under "Bottom 50%"). $D_{Foreign}$ is an indicator variable that takes the value of one if the dealer ($P2$) is a foreign entity (i.e., not incorporated in Australia); all other variables are defined similarly to Table 7. Standard errors are estimated using the Newey-West procedure allowing for heteroskedasticity and autocorrelation. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent Variable: ΔH					
	Coefficient on $Shock$					
	Bottom 50%			Top 50%		
	Money Mkt	Treasury Bonds	Semi-Gov Bonds	Money Mkt	Treasury Bonds	Semi-Gov Bonds
$Reln^{*}_{P3,P2}$	0.0000	-0.0029	0.0060	0.0002	0.0017	0.0023
$Amount$	0.0002*	0.0001*	0.0122**	-0.0008	0.0016	-0.0000
$Size$	0.0001	0.0019	0.0162**	0.0009	-0.0006	-0.0042
$Comp$	0.0004	-0.0007	0.0075	-0.0000	-0.0001	0.0027
$D_{P3=ND}$	-0.0000	-0.0008	-0.0035	0.0003	0.0036*	0.0145**
ΔR	0.0009	0.0014**	0.0002	-0.0000	-0.0002	-0.0041
$D_{Foreign}$	-0.0001	-0.0033	-0.0000	0.0004*	0.0011**	0.008