Endogenous Market Structure: Over-the-Counter versus Exchange Trading *

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Abstract

For many assets, traders favor either over-the-counter (OTC) or centralized markets. This paper examines how traders' choice between these trading venues depends on asset and trader characteristics. Traders have private information with heterogeneous precision and their values depend on a common and idiosyncratic component. A trader's incentive to choose an OTC market depends on the benefit of learning the asset value and the potential cost due to price impact. Traders choose OTC markets over centralized exchanges when the idiosyncratic component dominates in asset values or their private information is sufficiently inaccurate, and thus, the benefit from learning is high. Market structures are endogenously determined by traders' individual market choices. This paper provides comparative statics of endogenous market structures. When traders are asymmetric, the OTC and centralized markets can coexist. Furthermore, the OTC market decreases information efficiency by being conducive to trade only between informed traders.

Keywords: Noncompetitive trading, Over-the-counter markets, Exchanges, Price impact, Liquidity, Efficiency

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1 Introduction

Over-the-counter markets have been an important alternative trading venue for many assets, goods, commodities, financial derivatives, and securities. In over-the-counter markets, buyers and sellers are paired and privately choose their own trading terms, while public exchanges use a centralized trading mechanism such as uniform-price auctions. Many commentators have raised concerns about the implications of the various market mechanisms for their role in facilitating information aggregation and efficiency. The goal of this paper is to examine these implications when traders individually choose a trading venue and the resulting market structure is endogenously formed by traders' choices.

Certain types of assets appear to be traded mostly in over-the-counter markets, whereas others have been traded in centralized exchanges. Corporate bonds, interest rate swaps, index derivatives, and many liquid financial products are mostly traded in over-the-counter markets, even with their standardized structures and high volumes of trade. For some assets, the over-the-counter and centralized markets coexist. For instance, foreign exchange is traded in both over-the-counter spot markets and centralized futures markets. A good portion of over-the-counter FOREX trading is in fast venues, such as Currenex, EBS, and Reuters, in which the foreign exchange spot price is generally the same as the price in centralized futures markets. This paper examines traders' incentives to choose over-the-counter markets and whether this type of trading venue can harm the efficiency of the economy.

This paper characterizes the endogenous market structure in which traders play a Bayesian Nash equilibrium in the over-the-counter and centralized trading venues. In the first period $t = 0$, each trader chooses to enter either a centralized market or an over-the-counter market that opens at $t = 1$. In the *centralized market*, all traders' demand and supply schedules determine the single market price. In the *over-the-counter market*, a pair of traders are matched to be pairwise stable; and then they trade bilaterally at a pair-specific price. Entering into the over-the-counter market, a trader observes types of others – the correlation between his and their asset valuations (buyers and sellers) and their information precision (informed and uninformed). In both the centralized market and over-the-counter bilateral trades, trade takes place in the uniform-price double auction, in which all traders simultaneously submit their (net) demand schedules $q_i(p) : p \mapsto \mathbb{R}$, and the trades clear at price p^* such that $\sum_i q_i(p^*) = 0$. Traders are uncertain about the value of a risky asset and receive a private signal about the value before any market opens. Signal precision can be heterogeneous among traders. Their asset valuations are interdependent and have two components: a common component, which is the same for all traders, and an idiosyncratic component, which can be correlated heterogeneously across traders. The common value component captures the asset return or a future price in the dynamic market. In turn, the idiosyncratic value component captures an individual portfolio return that is correlated to the asset traded. If traders' portfolios are correlated (e.g., they contain the same assets), then the trader's idiosyncratic values are also correlated.

This trading mechanism is the canonical model for non-competitive markets for divisible goods (e.g., Kyle (1989), Vives (2011), and Rostek and Weretka (2012)). The uniform-price double auction allows an explicit treatment of price impacts, which are the key equilibrium objects that determine traders' trading behaviors, as well as, the market choices. The literature based on the uniform-price mechanism so far has maintained a joint symmetry assumptions on traders risk aversions, the correlation in traders' asset values, and variance of values and uncertainty. Rostek and Yoon (2017) dispense with any symmetry restrictions to allow heterogeneity in all characteristics and primitives. One message in this paper is that heterogeneity in trader and asset characteristics matter for understanding traders' incentives to choose a market and endogenous market structure.

Heterogeneity in characteristics affects *liquidity* and *learning* for traders. Liquidity is measured by the price impact, which is endogenously defined as the change of price as a trader's demand increases by one unit in equilibrium.[1] Larger price impacts, i.e. lower liquidity, reduce traders' demands and lower their utilities. Allowing traders to condition their private information and prices, the demand schedule incorporates inference about values. Hence, price impact and inference are interdependent. Heterogeneous correlations and information precisions affect the liquidity and learning separately and determine the incentives for traders to choose an over-the-counter market.

The first result shows that when the idiosyncratic component dominates the common value, in the sense that if the dispersion of correlations is larger than the average level of correlations,[2] over-the-counter markets are more attractive to traders in terms of both learning and liquidity. Equilibrium price is a weighted average of traders' signals and thus aggregates *out* idiosyncratic components in centralized markets. When a trader's value relies more on the idiosyncratic value, he learns more about this component in an over-the-counter market. On the other hand, the liquidity incentive is independent of whether the common or idiosyncratic component dominates. An over-the-counter market allows a trader to choose a counterparty who would more likely have opposite trading needs (i.e., more negatively correlated asset values), so that the trader has a lower price impact, while the centralized price mitigates the difference between values of buyers and sellers. This effect is stronger when traders' asset values are interdependent through the idiosyncratic values rather than the common component.

The literature has studied various traders' incentives to trade in over-the-counter markets or alternative trading venues. Traders can benefit in over-the-counter trades by searching better

[1]Other frictions considered in the literature (e.g. search costs, a chance that bilateral trades fail, bid-ask spreads by dealers, etc.) can increase traders' incentives to choose centralized markets over over-the-counter markets, but the results in this paper still hold quantitatively.

[2]Suppose that $\rho_{i,j}$ denotes the correlation between individual asset values of two traders i, j. A trader i's value is correlated all other traders $\{\rho_{i,j}\}_{j\neq i}$. The variance of these correlation represents the idiosyncratic component in trader i's asset value, while the average of correlations represents the common component. See Section 2.

prices in an over-the-counter market (e.g., Vayanos and Wang (2007), Vayanos and Weill (2008), and Zhu (2013)) or by clearing their large trading needs that cannot be fully exhausted in the centralized market (e.g., Bessembinder and Venkataraman (2014), Ready (2014), and Degryse, Jon, and Kervel (2015)). In this paper, even when there is no difference in prices between an over-the-counter trade and centralized market, the over-the-counter market can open by traders' choices. This is because, for certain trader and asset characteristics, trading over-the-counter offers the benefit of improving learning and lowering price impact. Moreover, traders choose the over-the-counter market when the centralized exchange is competitive. These results show that the heterogeneous asset values of traders from large idiosyncratic value components are the new incentive of over-the-counter trading that this paper contributes to the literature.

Second, this paper shows that the incentives to choose over-the-counter versus centralized markets differ between informed and uninformed traders. Traders with low information precision (i.e., *uninformed traders*) benefit from an over-the-counter market because it helps them learn counterparties' information. On the other hand, the over-the-counter market discourages those whose asset values are less idiosyncratic or those with high information precision (i.e., *informed traders*) to participate, since it decreases the likelihood of meeting a counterparty to trade with and also may increase price impact. The trade-off between information and liquidity incentives in over-the-counter markets creates a cutoff level of information precision. If a trader's information precision is higher than the cutoff level, the liquidity incentive dominates and he chooses to trade in the centralized market. Likewise, with a precision lower than the cutoff, the learning incentive dominates and traders choose the over-the-counter market.

Taking into account that the market choice are individual, the over-the-counter market will attract uninformed traders or both informed and uninformed traders. In the over-the-counter matching, there are two structures of over-the-counter markets depending on a dominant incentive: When the learning incentive dominates for all traders, all prefer to trade with informed counterparties. An uninformed trader cannot be matched with his preferred counterparty, and thus, he chooses another uninformed counterparty instead. It creates a *same-type* (i.e., positive assortative) matching. On the other hand, if the dominant incentive differs between informed and uninformed, a *cross-type* (i.e., negative assortative) matching occurs. With an available centralized market, however, the cross-type matching does not occur in equilibrium. When an informed trader values low price impact more than improving learning, he is better off trading in the centralized market than in the over-the-counter trading with uninformed counterparties. With only uninformed traders entering in the over-the-counter market, information is not transmitted between the informed and uninformed traders and the over-the-counter market aggravates the information asymmetry in the economy.

Moreover, this paper shows that asymmetry in traders is necessary for the two trading venues to coexist in equilibrium. When traders asset values are interdependent with the same profile of correlations[3] and their information precisions are the same, the trading strategies and incentives in the market choices are symmetric for all traders. With these symmetric incentives, the endogenous distribution of traders in two trading venues has a corner solution, in the sense that either all traders choose the centralized market or all choose the over-the-counter market. With asymmetric traders, endogenizing market structure creates a fixed point problem between traders' incentives in market choices and the distribution of traders in two trading venues. Taking into account that the learning and liquidity incentives are functions of endogenized market structures, this paper identifies the types of traders trading in the over-the-counter market in equilibrium. The over-the-counter trading occurs between traders who have relatively smaller idiosyncratic value components or lower information precisions.

Lastly, this paper develops an algorithm to construct a pairwise stable over-the-counter matching when the asset characteristic is asymmetric across traders and shows that a stable matching exists with any arbitrary interdependence in traders' asset values. Although the existence of a stable equilibrium in one-sided matching is not trivial, traders' preference on counterparties following the ranking of negative correlations ensures that a pairwise stable over-the-counter matching exists. The stable matching may not be unique if some traders are indifferent between two or more counterparties, but it does not affect the qualitative results on the endogenous market structure and the identities of traders who are in each market.

The results in this paper help explain which traders choose the over-the-counter or centralized markets, which assets are traded in either type of trading venues, and when centralized and over-the-counter markets can coexist. Biais and Green (2007) show that transaction costs and liquidity are key determinants on why most trades for bonds are held in over-the-counter markets, while Attanasi, Centorrino, and Moscati (2016) explore the effects of lack of information in the over-the-counter market on efficiency. This is consistent with this paper's prediction. Many financial derivatives such as forwards contracts, interest rate swaps, or equity or credit linked securities are traded in over-the-counter markets, even though their trading volumes (liquidity) are large. When these products are held by traders until, or close to, the maturity, it suggests that the purpose of trading can be hedging of traders' outside portfolios so that they are idiosyncratically valued. On the other hand, centralized markets attract assets traded mostly by arbitrageurs or short-term investors, such as stocks or bonds with short maturity, which are valued by future prices that are common to all traders. High-yield bonds that have low credit ranking are often traded in the over-the-counter markets (e.g., Hendershott and Madhavan (2015)). Low past trading volume and volatile return prevent the traders' access to quality information, i.e., low information precision. Moreover, it is possible to increase the information asymmetry between insiders and other traders.

[3] Rostek and Weretka (2012) define a symmetric interdependence in traders' asset valuation by an *equicommonal model*, $\frac{1}{I-1}\sum_{j\neq i} Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \bar{\rho}$ for all i. The symmetry condition in this paper is stronger than the equicommonal model. The profiles of correlations $\{Corr(\tilde{\theta}_i, \tilde{\theta}_j)\}_{j\neq i}$ are the same for all traders i. However, the symmetric model incorporates the heterogeneous correlations $Corr(\tilde{\theta}_i, \tilde{\theta}_j)$ across pairs of traders (i, j).

Related Literature: Literature has developed theoretical frameworks for over-the-counter markets for a fixed market structure. How liquidity affects traders' behavior and efficiency are studied in the literature (e.g., Duffie, Garleanu, and Pedersen (2005), Vayanos and Weill (2008), Weill (2008), Atkeson, Eisfeldt, and Weill (2014)). Other studies show how private information is aggregated in over-the-counter markets (e.g., Duffie, Malamud, and Manso (2014), Maurin (2015), Babus and Kondor (2016), Back, Liu, and Teguia (2016)). In addition to these papers focusing on over-the-counter markets, several papers compare these two trading venues in terms of welfare or individual profit. Observing that an over-the-counter markets can dominate centralized markets in welfare terms, several authors examine determinants that favor either market: such as default, search friction, price impacts, or information asymmetry between sellers and buyers (e.g., Acharya and Bisin (2010), Malamud and Rostek (2014), Duffie and Wang (2016), and Glode and Opp (2017)). Praz (2015) and Zhu (2014) studies how the presence of an alternating trading venue affect equilibrium in centralized markets.

Another strand of the literature endogenizes the over-the-counter structure itself by studying incentives to choose a counterparty in over-the-counter markets (e.g., Duffie, Carleanu, and Pedersen (2005), Golosov, Lorenzoni, and Tsyvinski (2014), Farboodi (2015)). Golosov, Lorenzoni, and Tsyvinski (2014) consider a dynamic incentive of uninformed traders to learn information at a cost of low liquidity in trading with an informed counterparty. In this paper, the joint effect (not necessarily a trade-off) of learning and price impact is the main determinant of counterparty choice. The learning and liquidity effects exist in the static trading due to the heterogeneity in precision (informed and uninformed traders) and correlation (asset characteristics). On the other hand, with heterogeneous preferences, traders search for a counterparty who can provide a better surplus (Chang and Zhang (2016)) or a better price (in Zhu (2012)). This paper shows that traders can strictly prefer one market to the other market or a counterparty to others even though equilibrium prices are the same across. Hence, the role of heterogeneity in determinants of counterparty choice is new in the endogenous market structure that this paper contributes to the literature.

The model in Babus and Parlatore (2017) is close to this paper. The authors examine over-the-counter dealer networks when trading is based on a uniform-price double auction as in this paper. In their paper, the endogenous choice of a segmented market (or the choice of a dealer) is determined by a trade-off between the price impact and the level of uncertainty in asset values. The contribution of this paper, compared to Babus and Parlatore (2017), is introducing a heterogeneous learning effect in endogenous over-the-counter matching and also in endogenous market choice.

The objective of this paper is to understand endogenous market structures when centralized and over-the-counter markets are both available. The choice between centralized and over-the-counter markets has been explored by several authors. Up to my knowledge, this paper is first to consider the market formation by all traders. Kirilenko (2000) and Viswanathan and

Wang (2002) consider a choice between trading venues for dealers by non-strategic agents (e.g. designers, authorities, consumers) maximizing profit or efficiency of the market. Bolton, Santos, and Scheinkman (2015) consider an entry problem of an informed seller to either market: a centralized (organized) market or an over-the-counter market with uninformed dealers. In this paper, all buyers and sellers, informed and uninformed, strategically choose a trading venue. Endogenizing the market choices of all traders lets the advantage of over-the-counter markets to be functions of endogenized participation and distribution of heterogeneous traders in two markets, rather than functions of fixed market structures. Furthermore, no trader has an incentive to change his market choice given chances in equilibrium with all traders' market choices, which provides a notion of the market stability.

2 Model

This paper considers a static economy where two trading venues open simultaneously: a centralized market where all traders' bids are executed at a single market price and an over-the-counter market where a pair of traders are matched and they trade bilaterally at a pair-specific price. Figure 2.1 summarizes the economy. Before the markets are open ($t = 0$), traders can choose which market they would trade in. If a trader chooses the over-the-counter market, then he also chooses a counterparty he would like to trade with. The market choice and bilateral matching occur at the end of period $t = 0$. Traders can trade only once, in one market and with one counterparty if they are in the over-the-counter market. At trading period $t = 1$, two assets – a risky asset (asset) and a riskfree asset (numeraire) – are traded in both markets. The assets are perfectly divisible. Traders submit their demands to the market they chose at the entering period, and each market cleared independently. I describe the details below, including (1) traders and payoffs, (2) information, (3) markets, (4) strategies, and (5) equilibrium.

Strategic Traders: There are $I < \infty$ strategic traders. Each of trader has a constant absolute risk-aversion (CARA) utility on quantity trading q_i net of payment $-pq_i$, where p is the price in the market he participates in. The ex-post utility is define as

$$u_i(q_i, p) = -\exp\Big(-\mu(\tilde{\theta}_i q_i - pq_i)\Big).$$

Here, $\mu > 0$ is the risk-aversion that is common for all traders, and $\tilde{\theta}_i$ is the individual value of the risky asset for trader i that is randomly drawn from $\tilde{\theta}_i \sim \mathcal{N}(E[\tilde{\theta}_i], \sigma_\theta^2)$. The conditional expected utility is equivalent to the mean-variance utility:

$$E[u_i(q_i, p)|\cdot] = -\exp\Big(-\mu\big(E[\tilde{\theta}_i|\cdot]q_i - pq_i - \frac{\mu}{2}Var(\tilde{\theta}_i|\cdot)q_i^2\big)\Big). \tag{1}$$

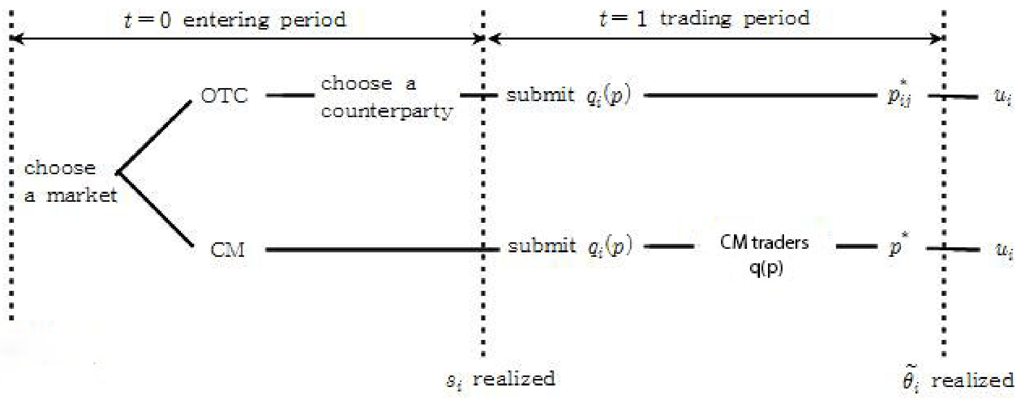

Figure 2.1: Timing of the economy. $q_i(p)$ is his quantity demand at a market price p. Trader i has a private information s_i before trading, and their individual asset value $\tilde{\theta}_i$ is realized at the end of economy and so does the utility u_i based on the realization of $\tilde{\theta}_i$ and equilibrium outcomes q_i, p^*.

In the CARA-Gaussian settings,[4] the conditional variance $V(\tilde{\theta}_i|\cdot)$ is a non-random constant independent of q_i, w_i or any realization in the markets, while the conditional expectation $E[\tilde{\theta}_i|\cdot]$ is a random variable that is determined by conditioning variables. Therefore, the expected utility (1) is equivalent to a *quadratic* utility with the coefficient on the first order term being random, which represented traders' expectation on asset value.

$$v_i(q_i, p) \equiv -\frac{1}{\mu}\log(-E[u_i(q_i)|\cdot]) = E[\tilde{\theta}_i|\cdot]q_i - pq_i - \frac{\mu}{2}Var(\tilde{\theta}_i|\cdot)q_i^2.$$

Traders' values $(\tilde{\theta}_i)_{i\in I}$ are interdependent. The correlation matrix for $(\tilde{\theta}_i)_i$ is denoted by $\widetilde{\Sigma} = (\tilde{\rho}_{ij})_{i,j\in I}$ with $\tilde{\rho}_{ij} \equiv Corr(\tilde{\theta}_i, \tilde{\theta}_j)$. The model allows any arbitrary Gaussian structure for traders' asset values. The interdependence of $(\theta_i)_i$ is interpreted as a combination of a *common value* component, which is attributed to the future asset return in the market, and an *idiosyncratic value* component, which comes from individual portfolio return consisting of other assets that are correlated to the trading asset in the market. The idiosyncratic value component is assumed to be independent to the common value component, but it can be correlated to other traders' idiosyncratic value components.[5] The decomposition of asset value $\tilde{\theta}_i$ is formalized as

[4]The CARA-normal settings is the standard of the non-competitive market literature. See Kyle (1989), Vives (2011), and Rostek and Weretka (2012). The non-competitive trading literature so far has focused on the cases when traders are symmetric in terms of asset valuations, interdependency, and/or information precision. One contribution of this paper is incorporating the heterogeneity in both interdependent asset valuation and information precision.

[5]This model with arbitrary interdependence of asset values can incorporates various interpretations and settings. For instance, as another interpretation of common and idiosyncratic value components: Each trader gets a random initial endowment before he enters the market, that can be correlated with other traders endowments. This private endowment forms his idiosyncratic value component. When the market has more trading rounds ($\tau > t = 1$) after the rounds we are considering in the model ($t = 1$), the asset value at t is determined by

follows:

$$\tilde{\theta}_i = \theta + \delta_i, \quad \forall\, i \in I,$$

where θ is the common value component and δ_i is the idiosyncratic value component of trader i. The common and idiosyncratic value components are independent and drawn from normal distribution, $\theta \sim \mathcal{N}(E[\theta], \sigma_{cv}^2)$ and $(\delta_i)_i \sim \mathcal{N}(0, \sigma_{iv}^2 \Sigma)$. The idiosyncratic values $(\delta_i)_i$ are interdependent by a correlation matrix,

$$\Sigma = \big(Corr(\delta_i, \delta_j)\big)_{i,j} = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1I} \\ \rho_{12} & 1 & \cdots & \rho_{2I} \\ \vdots & & \ddots & \vdots \\ \rho_{1I} & \rho_{2I} & \cdots & 1 \end{bmatrix}.$$

The correlations ρ_{ij} are *heterogeneous across pairs of traders* (i, j). I impose an assumption, without loss of generality, that the sum of correlations in a row $\sum_{j \neq i} \rho_{ij}$ is normalized to zero for all i. This is for keeping the heterogeneity from being additional source of common value, so that for making a clear separation of information aggregation.

Example 1 shows how the common value and idiosyncratic value components determine Σ in a simplest and intuitive setting.

Example 1 (Symmetric Interdependence in Asset Values) There are two groups of strategic traders – *buyers and sellers* – with equal group sizes.[6] Each trader has individual asset value that is decomposed into two independent random variables:

$$\tilde{\theta}_i = \theta + \delta_i = \begin{cases} \theta + \delta & \text{if } i \text{ is a buyer,} \\ \theta - \delta & \text{if } i \text{ is a seller.} \end{cases}$$

Suppose that $Var(\theta) = \sigma_{cv}^2$ and $Var(\delta) = \sigma_{iv}^2$. Then, the correlation matrix of idiosyncratic values $(\delta_i)_i$ is

$$\Sigma = \left[\begin{array}{c|c} \mathbf{1} & -\mathbf{1} \\ \hline -\mathbf{1} & \mathbf{1} \end{array}\right],$$

where each block represents $(\frac{I}{2} \times \frac{I}{2})$ matrix. From the distributions of common and idiosyncratic components, the correlation matrix of *total asset values* $(\tilde{\theta}_i)_i$ is

$$\widetilde{\Sigma} = \frac{1}{\sigma_{cv}^2 + \sigma_{iv}^2} \left[\begin{array}{c|c} \sigma_{cv}^2 + \sigma_{iv}^2 & \sigma_{cv}^2 - \sigma_{iv}^2 \\ \hline \sigma_{cv}^2 - \sigma_{iv}^2 & \sigma_{cv}^2 + \sigma_{iv}^2 \end{array}\right].$$

the marginal value function, which is a linear combination of individual asset return and future market prices. Hence, traders' valuation is interpreted as a combination of idiosyncratic value by holding the asset and common value by selling it at market price.

[6] Buyers and sellers are not explicitly determined in this model.

The interdependence of traders asset values is *symmetric* in this example, in the sense that the profile of correlation in each row is the same, $\{\rho_{ik}\}_{k\neq i} = \{\rho_{jk}\}_{k\neq j}$ for any $i \neq j$. However, the correlations $(\rho_{ij})_{i,j}$ are still heterogeneous across pairs of traders (i, j). I will consider this example for further analysis in Section 4, and will show the effects of the heterogeneous correlations across pairs and asymmetric interdependence across traders on endogenous market structures. □

INFORMATION: Each strategic trader gets a private information (signal) on his own valuation, $s_i = \tilde{\theta}_i + \varepsilon_i$ with an independent noise $\varepsilon_i \sim \mathcal{N}(0, \sigma^2_{i,\varepsilon})$. The information precision $\phi_i \equiv 1/\sigma^2_{i,\varepsilon}$ can differ across traders. The private signal s_i is realized at the beginning of trading period $t = 1$ and privately observed by trader i. The realizations of other traders' signals $(s_j)_{j\neq i}$ and prices in all markets are observed after all trades are done at the end of trading period $t = 1$.

Heterogeneity across traders, which is the key component in the model, is in both the correlation structure Σ and information precision $(\phi_i)_i$. Throughout this paper, I call this pair of asset and trader characteristics a *type*. Each trader's type represents his identity, such as buyers or sellers in Example 1. It is worth to remark that the type defined in this paper does not represent the realization of private signal s_i. This definition of type is different from the conventional definition in games with incomplete information. Traders' types and prior distribution of asset values and signals are common knowledge.

2.1 Centralized Market (CM) Mechanism

The centralized market is a large market where many buyers and sellers trade at a single price. I design the centralized market as a uniform-price double auction that is a canonical model in markets with divisible goods. A strategic trader i who enters the centralized exchange submits his net demand schedule $q_i(p) : \mathbb{R} \to \mathbb{R}$ (or a combination of limit and market orders) as a continuous function of price.

$$\max_{q_i(\cdot)} v_i(q_i, p) = \max_{q_i(\cdot)} \Big\{ E[\tilde{\theta}_i | s_i, p] q_i - p q_i - \frac{\mu}{2} Var(\tilde{\theta}_i | s_i, p) q_i^2 \Big\}, \quad \forall\, p \in \mathbb{R}. \tag{2}$$

Additional $L \geq 2$ traders, called *liquidity traders*, are introduced in the centralized market who are not given a choice to enter the over-the-counter market. Their presence ensures that the centralized market always function even when none of I strategic traders choose the centralized market.[7] The liquidity traders can be those who could not meet a requirement to enter the OTC, for example, not enough deposit or credibility. In a later section, I also show that liquidity

[7]Without this assumption on the presence of liquidity traders, there always exists a trivial equilibrium in which all strategic traders are in the over-the-counter market, independently of asset or trader characteristics. Two or more liquidity traders in the centralized market allows a strategic trader $i \in I$ who is currently in the over-the-counter market to consider an individual deviation to the centralized market.

traders can be those who do not observe other traders types so that they optimally choose to stay in the centralized exchange. Each liquidity trader submits their demand schedule $q_{lq}(p)$ based on his own private information. The precision of private information for liquidity traders are homogeneous and equal to the least informed traders: $\sigma^2_{lq,\epsilon} = \max_{i\in I} \sigma^2_{i,\varepsilon}$. Also, their asset values $\tilde{\theta}_{lq}$ are equal to the common value θ without any idiosyncratic value component. These assumptions on liquidity traders are to ensure that their presence does not affect the market choice of strategic traders $i \in I$.

After all demands are submitted, the centralized market is cleared at a price of which the total demand of I strategic traders and L liquidity traders is equal to zero; p^* such that $\sum_{i\in I} q_i(p^*) + \sum_{j\in L} q_{lq,j}(p^*) = 0$. The equilibrium allocation is determined by the demand schedule traders submitted, $q_i^* = q_i(p^*)$ for any $i \in (I \cup L)$.

2.2 Over-the-Counter Market (OTC) Mechanism

An over-the-counter market is an off-exchange trading venue in which bilateral trades occur between large institutions. Each trader who is in the over-the-counter market chooses a desired counterparty based on their types, information precision, and correlation. The choice should be mutual for two traders to be matched, in the sense that the over-the-counter matching is *pairwise stable*.[8] Each trader has an individual ranking on other traders, and based on the ranking, the matching will be determined by the algorithm of Irving (1985). If two traders are matched, they trade and leave the market. If the counterparty choice is not mutual, the matching fails and the trader searches for another counterparty until he succeeds at matching. I assume that the search cost is zero to focus on the difference of endogenous incentives in two trading venues. The over-the-counter market ends when all traders participate in exactly one bilateral trade or when only a single trader is left.

Once the matching occurs, each bilateral trade is operated by the same mechanism as in the centralized market: the uniform price double auction. Two traders simultaneously submit their demand schedules $q_i(p)$ as functions of price p by solving the optimization problem (2). The equilibrium price p_{ij} is determined by the market clearing condition: $q_i(p_{ij}) + q_j(p_{ij}) = 0$. The price p_{ij} is pair-specific in the over-the-counter market. If an equilibrium price does not exist, then there is no trade and the over-the-counter market ends without any further trade. The utility of traders in such case are set to be the autarky utility $v_i(q_i = 0) = 0$.

[8] The equivalence is due to the fact that traders' private signals are realized after their choice of the counterparty, and thus, the over-the-counter matching is determined by traders' ex-ante utility in the trade with each potential counterparty.

2.3 Market Choice and Trading

Based on the trading mechanisms in two markets described in Section 2.1 and 2.2, the strategies of traders and equilibrium are determined.

Strategies: At $t = 0$, each strategic trader $i \in I$ chooses a market where he enters, $m_i \in \{OTC, CM\}$ and a type of counterparty τ_i upon his entering to the over-the-counter exchange $m_i = OTC$. When the market choice of a trader is $m_i = CM$, we will notate $\tau_i = \emptyset$ for the convenience. At $t = 1$, the trader chooses his demand function $q_i(\cdot : m_i, \tau_i)$ in market (m_i, τ_i). Therefore, the strategy profile of trader i is $\{(m_i, \tau_i), q_i(\cdot : m_i, \tau_i)\}$. A liquidity trader $j \in L$ in the centralized market has a strategy $\{(CM, \emptyset), q_j(\cdot; CM, \emptyset)\}$ since she cannot enter the over-the-counter market.

Equilibrium: Definition 1 provides three conditions for equilibrium: (i) Bayesian Nash equilibrium in the double auction in each market, (ii) no incentive to deviate from the over-the-counter market to the centralized market, and (iii) pairwise stable over-the-counter matching including a pairwise deviation from the centralized to over-the-counter market. For each trader $i \in I$, $E[u_i(m_i, \tau_i)]$ denotes the expected utility with (m_i, τ_i) for given equilibrium distribution of traders in both markets.

Definition 1 (Equilibrium) *An equilibrium is defined by* $\{(m_i, \tau_i), q_i(\cdot : m_i, \tau_i)\}_{i \in (I \cup L)}$ *such that*

(i) traders' optimal bid schedules $\{q^i(\cdot : m_i, \tau_i)\}_i$ *solving the optimization problem (2) characterize a Bayesian Nash equilibrium in each market;*

(ii) no trader in the over-the-counter market has a strictly positive incentive to deviate to the centralized market: i.e., if $(m_i^*, \tau_i^*) = (OTC, \tau_i^*)$ *for trader* i*, then*

$$E[u_i(m_i^*, \tau_i^*)] \geq E[u_i(CM, \emptyset)], \quad \forall i \in I; \quad \textit{and}$$

(iii) the over-the-counter matching is pairwise stable: i.e., there exists no pair of traders (i, j) *who are not matched such that both traders* i *and* j *strictly benefit from breaking their respective matchings and creating a new matching between them.*

$$E[u_i(m_i^*, \tau_i^*)] \geq E[u_i(OTC, j)] \quad \textit{or} \quad E[u_j(m_j^*, \tau_j^*)] \geq E[u_j(OTC, i)], \qquad \forall i \neq j \in I.$$

The inequalities in Definition 1 (iii) include the case where either trader i or j (or both) choose the centralized market, $m_i^* = CM$ or $m_j^* = CM$, in equilibrium. This equilibrium condition ensures that the over-the-counter matching is immune to an entry of a trader from the centralized market as well as within the over-the-counter counterparty choice. Furthermore, with this pairwise deviation from the over-the-counter to centralized market, a market structure where all traders choosing the centralized market (i.e. $m_i^* = CM$ for all i) is a trivial equilibrium, independently of asset or trader characteristics.

The following sections characterize equilibrium defined in Definition 1: Equilibrium bid strategies and outcomes in Bayesian Nash equilibrium for a given market - part (i) - is characterized in Section 3. The characterization allows us to develop comparative statics on traders' expected utilities over the market, asset, or traders characteristics. Section 4 and 5 show endogenous market structures that are formed by traders' market and counterparty choice - part (ii) and (iii) - and analyze influences of the characteristics in traders' market choices and thus in endogenous market structures.

3 Equilibrium in Double Auctions

This section shows traders' bidding strategies in a given market. Equilibrium characterization in a market provides traders' equilibrium utility and its dependence on market, asset, or trader characteristics.

Suppose that there are N traders in a market with a correlation structure of asset values $\widetilde{\Sigma}$ and information precision $\{\phi_i\}_i$. Each trader i maximizes his expected utility as in equation (1). The first order condition is characterized as follows:

$$E[\tilde{\theta}_i|s_i,p] - \mu Var(\tilde{\theta}_i|s_i,p)q_i - p - \lambda_i q_i = 0, \quad \forall\, p \in \mathbb{R}, \tag{3}$$

where $\lambda_i \equiv \partial p/\partial q^i$ is the *price impact* that represents the change of price when trader i increases his demand by one unit. A larger price impact implies that each unit of a trader's demand leads to a further increase in equilibrium price so that the trader's demand is reduced by higher price impact. This demand reduction due to the price impact represents *market illiquidity* that is endogenously determined by the traders' strategies. A competitive market with infinitely many traders is perfectly liquid and the price impact is zero. In terms of primitives, when there are fewer traders in the market or when traders are more sensitive to price changes due to inference or risk-aversion, the market becomes less liquid.

In a trader' first-order condition (3), he takes an expectation of asset value conditioning on the equilibrium price p, as well as, his own private information. A trader chooses his bid at each potential realization of price, and thus, his behavior incorporates the information revealed by the price as if he observed the price. Therefore, even in the static model, traders make inference about their asset values by the schedule bidding.

Proposition 1 states three equilibrium conditions for a given market with N traders whose asset values are correlated by Σ and whose information precisions are $\{\phi_i\}_i$: (i) a trader's strategy for a given price impact (illiquidity) and inference on asset values (learning); (ii) the consistency condition for equilibrium price impact; and (iii) the inference coefficients by equilibrium price distribution.

Proposition 1 (Equilibrium Representation in a Market) *In a market, a profile of demand schedules $\{q_i(\cdot)\}_i$ is a linear Bayesian Nash equilibrium (hereafter, equilibrium) if*

(i) a demand schedule $q_i(\cdot : \lambda_i)$ maximizing trader i's utility is

$$q_i = \frac{E[\tilde{\theta}_i|s_i,p]-p}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda_i} = \frac{c_{\theta,i}E[\theta_i]+c_{s,i}s_i-(1-c_{p,i})p}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda_i},$$

where $E[\tilde{\theta}_i|s_i,p] = c_{\theta,i}E[\theta_i]+c_{s,i}s_i+c_{p,i}p$,

(ii) price impacts satisfy the consistency condition

$$\lambda_i = -\Big(\sum_{j\neq i}\frac{\partial q_j(\cdot)}{\partial p}\Big)^{-1} = \Big(\sum_{j\neq i}\frac{1-c_{p,j}}{\mu_i Var(\tilde{\theta}_j|s_j,p)+\lambda_j}\Big)^{-1} \geq 0, \quad \forall i, \tag{4}$$

(iii) inference coefficients $\{c_{\theta,i},c_{s,i},c_{p,i}\}$ in $E[\tilde{\theta}_i|s_i,p]$ and conditional variance $Var(\tilde{\theta}_i|s_i,p)$ are determined by the Projection Theorem, with equilibrium price distribution following

$$p = (\sum_i \frac{1-c_{p,i}}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda_i})^{-1}\sum_i \frac{c_{\theta,i}E[\theta_i]+c_{s,i}s_i}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda_i}.$$

A trader' indirect utility in equilbrium can be written as a function of his price impact λ_i, expected asset value $E[\tilde{\theta}_i|s_i,p]$ conditioning on (s_i,p), and conditional variable $Var(\tilde{\theta}_i|s_i,p)$. Ex-ante utility of trader i in a give market is

$$E[u_i] = E\Big[-\exp\Big(-\mu(\frac{\mu Var(\tilde{\theta}|s_i,p)+2\lambda_i}{2(\mu Var(\tilde{\tilde{\theta}}_i|s_i,p)+\lambda_i)^2}(E[\tilde{\theta}_i|s_i,p]-p)^2)\Big)\Big].$$

The Gaussian structure of $\{\tilde{\theta}_i,s_i\}_i$ generates the difference in individual expected asset value from equilibrium price, $(E[\tilde{\theta}_i|s_i,p]-p)$, follows a normal distribution. Thus, the expectation on the right hand side of the above equation is in the form of the moment generating function for χ^2_k distribution. It provides an explicit formula for the ex-ante indirect utility:

$$E[u_i] = -\Big(1+\underbrace{\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}}_{\text{liquidity effect}}\underbrace{\frac{Var(E[\tilde{\theta}_i|s_i,p]-p)}{Var(\tilde{\theta}_i|s_i,p)}}_{\text{learning effect}}\Big)^{-1/2}, \quad \forall i. \tag{5}$$

Here, $\widehat{\lambda}_i \equiv (\mu Var(\tilde{\theta}_i|s_i,p))^{-1}\lambda_i$ is a normalized price impact by the quadratic coefficient $\mu Var(\tilde{\theta}_i|s_i,p)$ of trader i's mean-variance utility. Trader i's ex-ante utility $E[u_i]$ can be decomposed into two parts: the value of liquidity and learning. The benefit of liquidity is captured by the term $(1+2\widehat{\lambda}_i)/(1+\widehat{\lambda}_i)^2 = 1-(\widehat{\lambda}_i/(1+\widehat{\lambda}_i))^2$. Recall that trader i's demand is reduced by a fraction $\widehat{\lambda}_i/(1+\widehat{\lambda}_i)$. In that,

$$q_i = \Big(1 - \frac{\lambda_i}{\mu Var(\theta_i|s_i,p)+\lambda_i}\Big)\frac{E[\tilde{\theta}_i|s_i,p]-p}{\mu Var(\tilde{\theta}_i|s_i,p)} = \Big(1-\frac{\widehat{\lambda}_i}{1+\widehat{\lambda}_i}\Big)q_i^{**}(p),$$

where $q_i^{**}(p)$ is the demand of trader i in a competitive market for a given price p. The demand reduction lowers utility with the same fraction. The liquidity benefit in utility terms, called *liquidity effect*, increases as the normalized price impact $\widehat{\lambda}_i$ increases. On the other hand, the utility (5) contains the term $Var(E[\tilde{\theta}_i|s_i,p]-p)/Var(\tilde{\theta}_i|s_i,p)$ that captures the benefit of learning from price and private information. Equilibrium price aggregates all market participants' private information on asset values. Traders learn the aggregated information from conditioning on price. It decreases the risk in uncertainty of the trader's own value θ_i and thus increases his expected utility through the term $Var(\tilde{\theta}_i|s_i,p)$. In addition, the price determines the net surplus $E[\tilde{\theta}_i|s_i,p]-p$ of buying a unit of asset. Such information on the future surplus influences the trader's utility through $Var(E[\tilde{\theta}_i|s_i,p]-p)$. The total benefit of learning the trader's own and others' valuation, called *learning effect*, is incorporated in a form of ratio in the expected utility (5).

3.1 Equilibrium Utilities: Learning and Price Impact

Now, this section characterizes the main objects of an equilibrium. Three characteristics can be considered in this model: market size (market characteristic), interdependence of traders' asset values (asset), and precision of private information (traders). Each characteristic affects learning and liquidity in traders' utilities. This section examines these effects of the three characteristics in a model with symmetric interdependent asset values and symmetric information precisions across traders.

Definition 2 (Symmetric Traders) *Traders are symmetric, if*

(i) the profile of correlations $\{\rho_{ij}\}_{j\neq i}$ is the same for all i; and

(ii) the information precision $\phi_i = \phi$ is the same for all i.

With the symmetric traders defined in Definition 2, traders submit symmetric strategies in each market, but the correlation of asset values is still heterogeneous across pairs, $Corr(\tilde{\theta}_i,\tilde{\theta}_j) = \rho_{ij}$ can differ for each pair (i,j), which is the key heterogeneity in traders' market choice. Asymmetric traders with asymmetric correlations and information precision will be considered in Section 5.[9] Example 2 and Proposition 2 show how the three key characteristics affect the ex-ante utility of each trader in symmetric markets.

Example 2 (Symmetric Interdependence and Precision) *Consider a market with N traders. All traders have a symmetric information precision $\phi_i = 1/\sigma^2_{i,\varepsilon} \equiv \phi$ and a symmetric average correlation to the residual market $\bar{\rho}_i = \frac{1}{I-1}\sum_{j\neq i}\rho_{ij} \equiv \bar{\rho}$ for all i. Each trader's optimal schedule and equilibrium price are*

$$\begin{aligned} q_i &= \frac{E[\tilde{\theta}_i|s_i,p]-p}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda} = \frac{c_\theta E[\theta]+c_s s_i-(1-c_p)p}{\mu Var(\tilde{\theta}_i|s_i,p)+\lambda}, \quad \forall\, i, \\ p &= \frac{1}{1-c_p}(c_\theta E[\theta]+c_s\frac{1}{I}\sum_i s_i) = \frac{1}{1-c_p}(c_\theta E[\theta]+c_s\bar{s}). \end{aligned}$$

Here, the liquidity and learning effects in trader i's ex-ante utility are characterized by the price impact and conditional variances:

$$\widehat{\lambda}_i = \frac{\lambda_i}{\mu Var(\tilde{\theta}_i|s_i,p)} = \frac{(1+(I-1)\bar{\rho})(1+\sigma^2-\bar{\rho})}{(I-2)(1+\sigma^2)+((I-1)^2+1-2(I-1)(1+\sigma^2))\bar{\rho}-(I-1)(I-2)\bar{\rho}^2},$$

$$Var(\tilde{\theta}_i|s_i,p) = \frac{(1+\sigma^2)+(I-2)\bar{\rho}-(I-1)\bar{\rho}^2}{(1+\sigma^2+(I-1)\bar{\rho})(1+\sigma^2-\bar{\rho})}\sigma^2_\varepsilon; \quad Var(E[\tilde{\theta}_i|s_i,p]-p) = \frac{(1-\bar{\rho})^2}{1+\sigma^2-\bar{\rho}}\frac{I-1}{I}\sigma^2_\theta.$$

Trader i gets the ex-ante utility $E[u_i] = -(1+\xi_i)^{-2}$ where

$$\xi_i = \frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}\frac{Var(E[\tilde{\theta}_i|s_i,p]-p)}{Var(\tilde{\theta}_i|s_i,p)}.$$

The liquidity effect on utility is captured by the term $\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}$. With this closed-form solution of inference parameters and price impact,

$$\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2} = 1-(\frac{\widehat{\lambda}_i}{1+\widehat{\lambda}_i})^2 = 1-\Big(\frac{(1+\sigma^2-\bar{\rho})(1+(I-1)\bar{\rho})}{(I-1)(1-\bar{\rho})(1+\sigma^2+(I-1)\bar{\rho})}\Big)^2.$$

The liquidity term increases as I increases or $\bar{\rho}$ decreases. Larger market size and/or more negative correlation with others on average results in more liquidity, and thus higher utility for traders. When the information precision $\phi = 1/\sigma^2$ increases, the endogenous liquidity of the market increases if $\bar{\rho} > 0$, and decreases if $\bar{\rho} < 0$.

[9] In asymmetric markets, in the sense that the profiles of correlations $\{\rho_{ij}\}_{j\neq i}$ are heterogeneous across traders, as well as, across pairs (i,j) and/or that information precision ϕ_i are heterogeneous, traders' optimal trading strategies are asymmetric. The effects of characteristics in traders' behavior and utilities in this section and the comparative statics on endogenous market structures in Section 4 can also be applied to asymmetric markets. This section focuses on the symmetric market, in order to avoid technical complexities.

The effect of learning from the price on utility is measured by

$$\frac{Var(E[\tilde{\theta}_i|s_i,p]-p)}{Var(\tilde{\theta}_i|s_i,p)} = \frac{I-1}{I}\frac{(1-\bar{\rho})^2(1+\sigma^2+(I-1)\bar{\rho})}{\sigma^2((1+\sigma^2)+(I-2)\bar{\rho}-(I-1)\bar{\rho}^2)},$$

which is increasing in information precision $\phi = 1/\sigma^2$. *The effect of average correlation* $\bar{\rho}$ *is ambiguous. The utility component due to learning is decreasing with respect to* $\bar{\rho}$, *if and only if,* $(1+\sigma^2)+(2I-3)(1+\sigma^2)\bar{\rho}+(I-3)(I-1)\bar{\rho}^2-(I-1)^2\bar{\rho}^3 > 0$. □

Proposition 2 characterizes the effects of each characteristic - market size, correlations, and information precision - on traders' expected utilities through learning and liquidity, when the other characteristics are fixed.

Proposition 2 (Liquidity and Learning Effects) *For a given market, the equilibrium utility of a trader* i *increases as*

(i) *the number of traders in market* N *is larger; or*

(ii) *asset values are more negatively correlated to price, i.e.,* $corr(\tilde{\theta}_i, p)$ *are more negative.*

The equilibrium utility is non-monotone in the average information precision, i.e.,

(iii) *information precision* $\phi^*_{-i} \in (0,\infty]$ *of other traders maximizes trader* i*'s utility.*

The effects of the number of traders (part (i)) on learning and liquidity have been studied in literature. In a sufficiently symmetric market, with more traders participating in the market, price reveals more accurate information. Moreover, price impact can be small in large markets, when other characteristics are fixed (See Rostek and Weretka (2012)). Proposition 2 (ii), however, suggests that the benefits of large markets in learning and liquidity are not necessarily true if traders in each market, large or small, have heterogeneous asset valuations. Suppose that the equilibrium price in a small market exhibits greater negative correlations with trader i's asset valuation. Price provides new information that is not captured in trader i's private information, and with larger correlation in the absolute sense implies that the information is more relevant to his asset value. This learning effect is captured by the decrease in conditional variance $V(\tilde{\theta}_i|s_i,p)$. The correlation structure also affects the liquidity through the endogenous price impacts λ_i. The price impact is characterized by the slope of the residual supply curve, $\lambda_i = -\big(\sum_{j\neq i}\partial q_j(\cdot)/\partial p\big)^{-1}$, that is an inverse of the aggregate reaction of other traders when price increases. With more negative correlations, trader $j \neq i$ would rely more on the price for his inference, in the sense that $c_{p,j}$ is more negative. This makes his demand more elastic to price change and thus trader i's price impact is smaller. Hence, his equilibrium utility increases due to both learning and liquidity as the correlation between his asset values and price is more negative. From the arguments, more negative correlations between traders' asset values and/or more traders in the market are beneficial to both learning and liquidity. These conditions of two characteristics jointly determine traders' incentives to choose a market, which will be examined in the next Section 4.

In addition to the joint condition of market size and interdependent asset valuation, the last characteristic that affects equilibrium is the precision of traders' private information. Information precision has an ambiguous influence on traders' expected utilities. The value of learning increases when the trader's own information precision is lower or when the (weighted) average of other traders' information precision is higher. At the same time, the price impact increases, and thus, the liquidity decreases. It creates a *trade-off* between learning and liquidity when the precision of information from the price changes. The trade-off between learning and liquidity over traders' information precision is shown in Figure 3.1. As a result, trader i's utility is non-monotone with respect to the other other traders' information precision. If his precision is sufficiently low, the learning effect dominates the liquidity effect, so that his utility is monotonically increasing in others' precision.

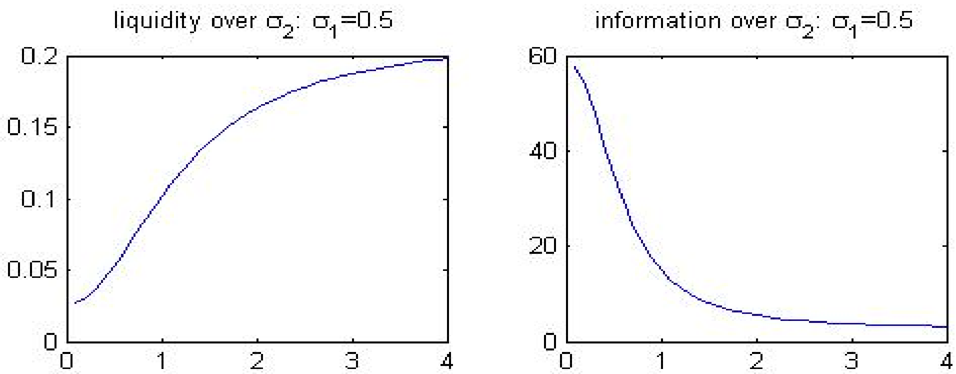

Figure 3.1: Liquidity and learning effects with respect to other traders' information precision $1/\sigma_2$. A trader i has a information precision $\phi_1 = 1/\sigma_1^2 = 1/0.25 = 4$. The liquidity effect and the learning effect in his expected utility (5) are shown in each graph respectively. Two effects are monotone over the other traders' information precision $\phi_2 = 1/\sigma_2 \equiv avg(1/\sigma_j^2)_{j\neq 1}$.

The comparative statics show the types of traders who would enter an over-the-counter market based on the interdependence of asset values and the precision of their information. The ambiguity in the influence of information precision on traders' utilities will be considered as a key determinant of traders' market and counterparty choices.

4 Endogenous Market Structure

Traders' individual choice for markets and counterparties forms a distribution of traders' types in centralized and over-the-counter markets and also an over-the-counter matching. This is called a *market structure*. This section characterizes endogenous market structures by using the comparative statics developed in the previous section. There are three types of market structure: only centralized market opens, only the over-the-counter market opens, and both markets co-exist. Example 2 with a competitive centralized market (i.e. perfectly liquid market with $\lambda_i = 0$ for all i) provides some intuition on endogenous market structures. The competitive centralized market maximizes the difference in market sizes. The example shows that traders can still be attracted to the over-the-counter market with certain condition for asset and trader characteristics.

Example 1 & 2 - Cont'd *Equation (5) provides the explicit formula of expected utility when there are N symmetric traders. The utility from the centralized trading is derived by taking N to infinity, while the utility from a bilateral trades in the over-the-counter market is by setting $N = 2$. With these ex-ante utilities in two exchanges, trader i chooses which exchange he wants to participate in. Under the equilibrium existence, the necessary and sufficient condition for him to enter the over-the-counter exchange is as follows:*

$$E[u_i^{CM}] < E[u_i^{OTC}] \quad \Leftrightarrow \quad \frac{1-\bar{\rho}_{CM}}{\sigma^2} < \frac{-2\rho_{OTC}}{1+\sigma^2+\rho_{OTC}}\mathbf{1}_{\{\rho_{OTC}<0\}}.$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function. Here, $\bar{\rho}_{CM} = \frac{\sigma_{cv}^2}{\sigma_{cv}^2+\sigma_{iv}^2}$ is the average correlation in the centralized market and $\rho_{OTC} = \frac{\sigma_{cv}^2-\sigma_{iv}^2\rho}{\sigma_{cv}^2+\sigma_{iv}^2}$ is the correlation between two traders who are matched in the over-the-counter market, which are sufficient statistics on $Corr(\tilde{\theta}_i, p)$ in two markets. Consider the following canonical assumptions on traders' asset valuation:

- *Independent Private Value: $\sigma_{cv}^2 = 0, \sigma_{iv}^2 = 1$, and $\rho = 0$. With independent private (idiosyncratic) value, traders get no gain-to-trade in the over-the-counter market, i.e., $\frac{-2\rho_{OTC}}{1+\sigma^2+\rho_{OTC}}\mathbf{1}_{\rho_{OTC}<0} = 0$, while they get strictly positive equilibrium utility $1/\sigma^2$. Therefore, all traders choose the centralized market, and the over-the-counter market does not open. Independent private value structure implies that the market has no valuable information to any trader (no learning occurs), so all traders choose the centralized market to benefit from the liquidity.*

- *Fundamental Value (Vives (2011)): $\sigma_{cv}^2 = 1-a, \sigma_{iv}^2 = a$ with a constant $a \in (0,1)$, and $\rho = 0$. Taking $a \to 0$, the fundamental value model includes the common value: $\tilde{\theta}_i = \theta$ for all i. With the fundamental value model, the over-the-counter trade provides no gain-to-trade since $\rho_{OTC} > 0$. On the other hand, traders get strictly positive equilibrium utility ϵ/σ^2, and thus, all traders choose the centralized market. The over-the-counter market does not exist. Fundamental value model does not incorporate heterogeneous correlations across pairs of traders, in the sense that $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \frac{\sigma_{cv}^2}{\sigma_{cv}^2+\sigma_{iv}^2}$ for any pair (i, j). Hence, it concludes that the heterogeneous correlation is necessary for a trader to choose the over-the-counter market.*

- *Two-Sided Market with Buyers and Sellers (Example 1): $\sigma_{cv}^2 = 1-a, \sigma_{iv}^2 = a$, and $\rho = \pm 1$.*

Traders choose the over-the-counter market if and only if

$$\frac{a}{\sigma^2} < \frac{4a-2}{2-2a+\sigma^2} \quad \Leftrightarrow \quad \underbrace{a > \frac{2-3\sigma^2+\sqrt{(2+3\sigma^2)^2-8\sigma^2}}{4} > \frac{1}{2}}_{\textit{iv is sufficiently large}} \quad \textit{and} \quad \underbrace{\frac{2a(1-a)}{3a-2} < \sigma^2}_{\textit{precision is sufficiently low}}. \tag{6}$$

Traders prefer to trade in the over-the-counter market if the idiosyncratic value component in asset values is sufficiently large and the information precision is sufficiently small.

When the centralized exchange is competitive, the liquidity incentive strongly derives traders to avoid higher price impacts in over-the-counter bilateral trades. Hence, participation to the over-the-counter market occurs only when the benefit of learning from the market is high enough to dominate the loss from illiquidity. When the aggregated correlation $\bar{\rho}_{CM} = \frac{1}{I-1}\sum_{j\neq i}\rho_{ij}$ *satisfies* $|\bar{\rho}_{CM}| < |\rho|$, *the price informativeness is higher in the over-the-counter exchange and thus the benefit from learning is higher.* □

The predictions from the above example hold generally in the model with a non-competitive centralized market and/or with asymmetric traders. (i) Traders choose the over-the-counter market over the centralized market if the idiosyncratic value component in asset values is sufficiently large and the information precision is sufficiently small; (ii) The over-the-counter market does not exist if there is no heterogeneity across traders' asset valuation.

Proposition 2 showed that equilibrium utility of a trader increases as the number of traders who are participating in the market increases or as the correlation between his asset value and the market price is more negative. With the presence of $L \geq 2$ liquidity traders in the centralized market the number of traders (hereafter, market size) is larger in the centralized market and its effect encourages traders to enter into the centralized market. However, the effect of correlation between asset value and price is the opposite. In the over-the-counter market, a trader can target a counterparty that has the most negative correlation, while the correlation with the CM price is determined by the average correlation over all participants. Hence, the effect of correlation $Corr(\tilde{\theta}_i, p)$ supports traders choosing the over-the-counter market. It is worth emphasizing that from the comparative statics in Proposition 2, the correlation effect reduces the price impact, as well as, improves learning. Hence, the benefit of more negative correlation in the over-the-counter market is not only from better learning but also from low price impact.

The effects of market size and correlation create a trade-off in the traders' choice of market. Theorem 1 examines when the correlation effect would dominate and provides a sufficient and necessary condition such that the trader prefers to trade in the over-the-counter market and endogenous market structure following the traders' individual market choices.

	OTC		CM
# of trader	2	$<$	$L+I$
$corr(\tilde{\theta}_i, p)$	$corr(\tilde{\theta}_i, \tilde{\theta}_j)$	$<$	$\frac{1}{I-1}\sum_{j\neq i} corr(\tilde{\theta}_i, \tilde{\theta}_j)$

Table 1: Traders' market choices and trade-off between market sizes and correlations

Theorem 1 (Endogenous Market Structure) *The over-the-counter market opens in equilibrium by some traders entering into the market, if and only if*

$$\sigma_{iv}^2/(\sigma_{cv}^2+\sigma_{iv}^2) \;>\; \hat{\kappa}(\{\phi_i\}_i, \Sigma) \quad \text{and} \quad \phi_i = 1/\sigma_{i,\varepsilon}^2 \;<\; \hat{\phi}_i(\sigma_{cv}, \sigma_{iv}, \Sigma)$$

for some bounds $\hat{\kappa} < \infty$ and $\hat{\phi}_i > 0$.

The first inequality in Theorem 1 implies that traders choose the over-the-counter market when their asset values are sufficiently heterogeneous by having a large variance of idiosyncratic value component $\sigma_{iv}^2/(\sigma_{cv}^2+\sigma_{iv}^2)$. It implies that the targeted bilateral trades in the over-the-counter market can benefit a trader, in terms of both learning and price impact. Suppose that a trader (say, a buyer) has a negative correlation with sellers but has a positive correlation with another buyer. When both buyers and sellers participate in the centralized market, the price that aggregates values of all traders mitigates the correlation so that the average correlation $\bar{\rho}$ gets closer to zero. In a bilateral trade, the correlation with a single counterparty (i.e. seller) can demonstrate a greater negative value than the average correlation in the centralized market. The difference between these correlations can be enhanced when the asset valuation relies more on the idiosyncratic value component than the common value component. This helps explain why assets that have a strong common value component tend to be traded in the centralized market, while assets that are heterogeneously valued tend to be traded in the over-the-counter market. Furthermore, the second inequality condition in Theorem 1 shows that the dominance of correlation effect is strengthened by low information precision. This is because the trader's inference depends more on the price, so the difference between correlations is emphasized more in the trade-off between the effects of market size and correlations. The low information precision, *a characteristic of traders*, creates a joint condition with the sufficiently heterogeneous asset valuation, *a characteristic of assets*, for the over-the-counter market to be chosen by traders in endogenous market structure.

The predictions in Theorem 1 are consistent with financial markets. Many over-the-counter products, such as forward contracts or corporate bonds, are traded for the purpose of hedging. The portfolio they need to diversify is idiosyncratic so that asset values are valued by idiosyncratic value components. On the other hand, stocks or options that are often traded by speculators are valued by the common values, which are the future prices in the market.[10] It should be noted that the condition for over-the-counter markets to exist is a joint condition on asset valuation and information precision. Bonds with low credit rating, which traders would not have precise information due to its volatile value, are often traded in over-the-counter markets. Alternatively, treasuries and high ranked bonds are also traded in centralized futures markets, even though they are valued idiosyncratically.

The following two corollaries show some properties of traders' market choice and endogenous market structure, other than learning and liquidity in this paper. These properties have been studied in literature. Namely, the literature has shown that the over-the-counter markets can be beneficial for (i) providing an additional trading opportunity to traders who could not fully clear their trading needs in centralized markets, and for (ii) allowing traders to search for better prices than the centralized market price. Despite these benefits of trading in over-the-counter markets being present in this model, Corollary 1 and 2 show that the over-the-counter market can be still chosen by traders even without the illiquidity in centralized markets or the price difference between trading venues.

Corollary 1 (OTC with a Competitive CM) *Suppose that the centralized market is competitive, i.e., the number of liquidity traders is large, $L \to \infty$. There exists a set of correlation Σ and precision ϕ, satisfying the inequalities (6), such that all strategic traders choose the over-the-counter market over the competitive centralized market.*

Corollary 1, as seen in Example 2 - Cont'd, shows that traders may prefer to trade in the over-the-counter market even when the centralized market is perfectly liquid, and thus, all traders choose to trade over-the-counter and only liquidity traders participate in the centralized market. Recent studies (e.g., Bessembinder and Venkataraman (2014), Ready (2014), and Degryse, Jong, and Kervel (2015)) show that the over-the-counter market or off-exchange trading venues can open because of the illiquidity (i.e. non-competitiveness) of centralized markets: Trading needs of institutions who have large endowments may not be fully absorbed in the centralized market, and thus, these traders would trade in all available trading venues subject to the entry costs. An over-the-counter market is a platform that provides more trading opportunities. Traders' improved learning about heterogeneous asset values can favor the choice of an over-the-counter market, even if the price impact were lower in the centralized market.

Corollary 2 (No Price Difference in OTC and CM) *There exists a set of primitives such that the expected prices are the same in two markets and traders choose the over-the-counter market.*

[10] Another canonical example on over-the-counter products is a housing market. Even though the unit demand for houses does not directly fit the divisible good model in this paper, the intuition carries over. Houses are valued in different aspects by different traders, and through brokers, the over-the-counter market matches a buyer and a seller who have highly correlated valuations.

Literature that studies an over-the-counter market mechanism with search and bargaining (e.g., Zhu (2013), Vayanos and Wang (2007), and Vayanos and Weill (2008)) shows that traders choose to trade in over-the-counter markets when searching for better prices. Traders can choose an over-the-counter market even when the prices in the two markets are the same (Corollary 2). This is because, for certain traders and asset characteristics, trading in over-the-counter markets offers improved learning and lower price impact.

5 Market Structure with Asymmetric Traders

Theorem 1 examined a trader's choice between the over-the-counter and centralized markets and the endogenous market structures. The key characteristics is the heterogeneous correlations in asset valuation $Corr(\tilde{\theta}_i, \tilde{\theta}_j)$ across pairs of traders (i, j). This section considers the effects of other types of heterogeneities: namely, heterogeneous correlations across traders, not only across pairs, and heterogeneous information precision. A model with such heterogeneities across traders is called an *asymmetric* model, and a model without the heterogeneities a *symmetric* model (See Definition 2).

With symmetric traders, all bilateral matches in the over-the-counter market are identical in the sense that the correlation between two matched traders is the same for all pairs and $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \min_{j \neq i} Corr(\tilde{\theta}_i, \tilde{\theta}_j)$ for any i. It leads all traders to have equal incentives to choose either market by fixing the correlation difference between the two markets to be symmetric for all traders. All strategic traders are symmetric in the market choice. On the other hand, the incentives to choose either market can differ by traders in asymmetric markets, and thus, the incentives of traders in the choice of the market are functions of distribution of traders in two markets as well as of endogenized market structure. The next theorem shows that the asymmetry across traders is necessary for the coexistence of two trading venues: the over-the-counter and centralized markets.

Theorem 2 (Coexistence of CM and OTC) *The centralized and over-the-counter market coexist in equilibrium only if traders are asymmetric.*

Suppose that a trader gains from deviating from the over-the-counter to centralized market. His deviation increases the market size in the centralized market. With the fixed correlation difference as discussed above, the incentive to deviate from the over-the-counter market to the centralized market for the next trader is even stronger. Recursively, all traders end up choosing the centralized market. The deviation from the centralized market to the over-the-counter market follows the similar argument, by recursively increasing incentives to deviate due to decreasing market size in the centralized market. It concludes that the endogenous distribution of traders in two trading venues has a *corner* solution when traders are symmetric. Equivalently, the over-the-counter and centralized markets can coexist in equilibrium only if traders are asymmetric: in the sense that either (i) the profile of correlations $\{\rho_{ij}\}_{j\neq i}$ is asymmetric or (ii) the information precision ϕ_i is asymmetric across traders.

In an endogenous market structure in which both trading venues coexist, some strategic traders choose the over-the-counter market while other traders choose the centralized market. The next sections examine which types of traders are more attracted to the over-the-counter market versus which are more attracted to the centralized market. Section 5.1 explores the effect of heterogeneous correlation profiles and Section 5.2 examines the heterogeneous information precision in both endogenous over-the-counter matching and market structure.[11]

5.1 Asymmetric Interdependence of Asset Valuations

Suppose that traders are asymmetric in the sense that their profiles of correlation $\{\rho_{ij}\}_{j\neq i}$ differ. In the over-the-counter market, each trader can choose his counterparty based on the type, i.e. correlation structure. The matching fails if the choice of the counterparty is not mutual. In addition, even when two traders are matched, the trade does not occur if the traders have positively correlated asset values. In that, if $Corr(\theta_i, \theta_j) = \rho_0 > 0$, traders optimal bid function becomes inelastic so that there is no trade. No trader chooses a counterparty whose values are positively correlated with his. Consequently, if a trader i's asset value satisfies $Corr(\tilde{\theta}_i, \tilde{\theta}_j) > 0$ for any $j \neq i$, i.e., his asset valuations are positively correlated with all other traders, then he gets zero gains-to-trade in the over-the-counter market which makes him enter the centralized market.

Recall that the over-the-counter matching is determined by traders' ranking on counterparties and that a trader prefers to trade with the one whose value is more negatively correlated with his. Traders who have relatively less negative correlations may not be matched with whom he wants, or he may not be matched with anyone. These traders will not be chosen by the ones that they want to be matched with. This lowers the benefit of the over-the-counter market and makes them choose the centralized market.

Proposition 3 (OTC Matching with Heterogeneous Correlations) *Suppose that traders are asymmetric in correlation structures but symmetric in information precision. There exists a pairwise stable over-the-counter matching determined by the ranking in the negative correlations* $(-Corr(\tilde{\theta}_i, \tilde{\theta}_j))$ *of pairs of traders.*

The pair-wise stable over-the-counter matching is determined by the following algorithm:

[11] Since their incentives in the choice of the market are functions of endogenized market structure, traders' market choice and endogenous market structure create a fixed point problem in equilibrium. This complexity makes it difficult to analyze endogenous market structure in general. Hence, the two-dimensional asymmetry - heterogeneous correlation profiles and heterogeneous information precision - will be considered separately. The results from each heterogeneity can be jointly studied in a model with an arbitrary correlation structure and information precisions.

STEP-1. Two traders, who have the most negative correlation among all pairs, are matched and the matching is denoted by (i_1, j_1). If there are multiple pairs that have the most negative correlation, select one pair randomly.

STEP-2. Eliminating the selected traders, select the most negative correlation among the remaining paper and create another pair: called (i_2, j_2).

STEP-3. Repeating this procedure until there is at most one remaining trader in the over-the-counter market, and then the over-the-counter matching is determined $\{(i_t, j_t)\}_{t=1,2,\cdots}$.

In general, a stable equilibrium may fail to exist in one-sided matching problems. However, if traders are asymmetric only in correlation structure, a pairwise stable over-the-counter matching always exists in endogenous market structure with the endogenized choice of market and counterparty. First, the ranking based on negative correlations in Proposition 3 guarantees the transitive property on ranking. It is shown by the fact that the rankings of traders do not create any circular preferences. Suppose that there exists traders i, j, and k whose rankings are circular: i prefers j to k, j prefers k to i, and k prefers i to j. By Proposition 3, it implies that $Corr(\tilde{\theta}_i, \tilde{\theta}_j) \leq Corr(\tilde{\theta}_i, \tilde{\theta}_k) < 0$, $Corr(\tilde{\theta}_j, \tilde{\theta}_k) \leq Corr(\tilde{\theta}_j, \tilde{\theta}_i) < 0$, and $Corr(\tilde{\theta}_k, \tilde{\theta}_i) \leq Corr(\tilde{\theta}_k, \tilde{\theta}_j) < 0$. Hence, the correlations between the three traders satisfy $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = Corr(\tilde{\theta}_j, \tilde{\theta}_k) = Corr(\tilde{\theta}_k, \tilde{\theta}_i)$, and thus, each trader is indifferent between the other traders in his counterparty choice. In addition to the stability, the individual market choice keeps a trader from not being matched in the over-the-counter market. A trader who fails to find a counterparty in the over-the-counter market deviates to the centralized market. Therefore, a stable over-the-counter matching exists in equilibrium due to the ranking mechanism in Proposition 3 and the endogenized market choice between over-the-counter and centralized markets.

5.2 Asymmetric Information Precision

In order to understand the effect of heterogeneity in information precision on endogenous market structure, suppose that traders are asymmetric only in information precisions but symmetric in the correlation structure, i.e., ϕ_i is different across i but the profile $\{\rho_{ij}\}_{j \neq i}$ is the same for all i. Proposition 2 (iii) shows that a trader's equilibrium utility is non-monotone over other traders' information precision. A trader prefers an informed counterparty to improve learning, but he would prefer an uninformed counterparty to have a lower price impact. Concerning this trade-off between learning and price impact over the information precision of counterparty, Proposition 4 shows how a trader ranks the counterparty depending on his own information precision.

Proposition 4 (Trade-Off in Learning and Price Impact over Precision) *In a bilateral matching between traders i and j, the equilibrium utility (5) of trader i satisfies that* *(i) the liquidity effect* $\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}$ *decreases in* ϕ_j*; and*

(ii) the learning effect $\frac{Var(E[\tilde{\theta}_i|s_i,p]-p)}{Var(\tilde{\theta}_i|s_i,p)}$ *increases in* ϕ_j*.*

The liquidity effect dominates the learning incentive if and only if the trader's own precision ϕ_i *is sufficiently high.*

In the trade-off between learning and price impact, which effect dominates depends on the trader's own precision. If trader i's own information precision is already high, lower price impact is more valuable than better learning so that he chooses a relatively less informed counterparty. On the other hand, if his precision is low he prefers a more informed counterparty for better learning. The trade-off between learning and liquidity gives a non-monotone preference on the counterparty's information precision, in the sense that the optimal counterparty's information precision $(\phi_{-i})_i^* = arg\max_{\phi_{-i}=1/\sigma_{-i}^2} E[u_i; OTC(i,j)]$ is determined in the interior of support $(\phi_{-i})_i^* \in (0,\infty)$ for traders with sufficiently large ϕ_i. Furthermore, the optimal counterparty's precision $(\phi_{-i})_i^*$ is decreasing in trader i's own precision ϕ_i.

It is useful to consider a model with two types of information precisions, informed and uninformed types. The information precisions of two types are assumed by $\phi_U = 1/\sigma_U^2 < \phi_I = 1/\sigma_I^2$. With two informational types, the over-the-counter matching is either positive assortative matching (i.e., *same-type* matching) or negative assortative matching (i.e., *cross-type* matching).[12] The same-type matching is when traders are matched with other traders with the same type, and cross-type matching is when informed and uninformed traders are matched to each other. Figure 5.1 presents regions of $\{\sigma_I, \sigma_U^2\}$ for the same-type and cross-type matching in equilibrium. First, consider the case where informed traders have sufficiently high precision (small σ_I) and uninformed traders have sufficiently low precision (large σ_U). Both types of traders choose to trade with the opposite type of counterparty, with different incentives: informed traders get benefit from liquidity incentive, and uninformed traders benefit from learning incentive. Hence, the cross-type matching occurs in equilibrium. Outside of this region, equilibrium shows the same-type matching. When the precision levels for both traders are high (small σ_I and σ_U), liquidity incentives dominate and all traders want to be matched with an uninformed counterparty. As a result, some informed traders can not be matched with their preferred counterparty. Since there is no more matching opportunity, the informed traders optimally shift their counterparty choice to a less preferred counterparty, informed traders. Hence, the same-type matching occurs in equilibrium. Proposition 6 in Appendix shows a sufficient and necessary condition for the cross-type matching equilibrium, in terms of information precision (σ_I, σ_U) and correlation structure Σ.

[12] The non-monotone ranking on counterparty's precision may prevent an assortative matching in over-the-counter markets. However, I am expecting that there exists an endogenous statistics in which the matching is assortative.

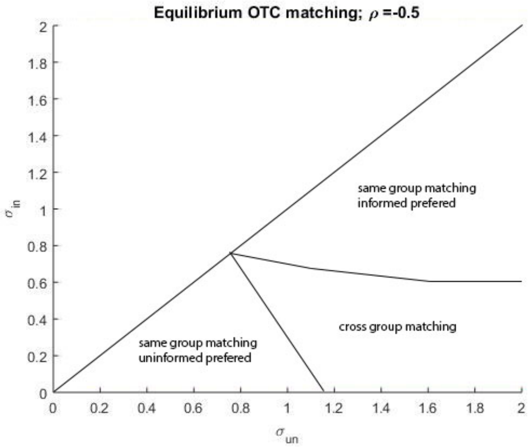

Figure 5.1: Equilibrium matching in OTC subgame: Each region shows an endogenous over-the-counter matching, either same-type matching or cross-type matching between informed and uninformed traders. All traders are assumed to be in the over-the-counter market. The x-axis is the noise variance of uninformed traders while the y-axis is of informed traders. $\sigma^2_{cv} = 0.25, \sigma^2_{iv} = 0.75$ and $\min_{j\neq i}\rho_{ij} = -1$.

With the presence of the centralized market, an over-the-counter market in which two informational types match does not exist. When the informed type follows lower price impact rather than better learning, he can be better off trading in the centralized market than in the over-the-counter trading with uninformed counterparties.

Proposition 5 (No Cross-Type OTC Matching) *Suppose that there are two precision types $\sigma^2_{\varepsilon,i} \in \{\sigma^2_{\varepsilon,in} < \sigma^2_{\varepsilon,un}\}$. With $\sigma^2_c > \hat{\sigma}^2 > 0$, there is no over-the-counter trade between informed and uninformed traders (i.e., cross-type matching).*

Figure 5.2 presents an example of endogenous market structures through traders' market and counterparty choice. The left panel three types of equilibrium: all traders choose the centralized market (when both σ_I and σ_U are small, and learning is not sufficiently valuable to either of them); only uninformed traders choose to trade in the over-the-counter market (large σ_U but small σ_I); and all traders choose the over the counter market (both types of traders have inaccurate information). Since learning incentive is a dominant incentive for uninformed traders, there is no equilibrium where only informed traders enter the over-the-counter market.

Endogenizing the market choice, the over-the-counter market will attract either the uninformed or both.[13] Furthermore, traders in the over-the-counter market always trade with the same-type counterparty. The non-existence of matching between informed and uninformed attributes to aggravating information asymmetry in over-the-counter markets. With a random

[13] The conventional wisdom that informed traders are more likely to trade in the over-the-counter market for keeping their private information from the public. Since this model considers only a static trading, such privacy incentive does not exist. The incentives to trade in the over-the-counter market due to the heterogeneity across traders is a separate effect. In dynamic models, I expect that the privacy incentives interact with the effects of heterogeneities.

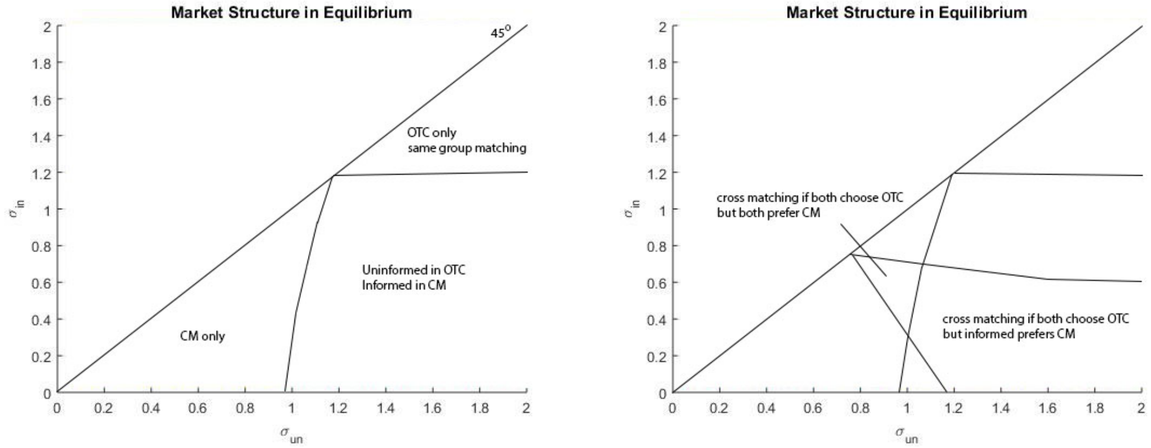

Figure 5.2: Endogenous Market Structure: The x-axis is the noise variance of uninformed traders while the y-axis is of informed traders. $\sigma_{cv}^2 = 0.25, \sigma_{iv}^2 = 0.75$ and $\min_{j \neq i} \rho_{ij} = -1$.

match mechanism, information can be transmitted from the informed to the uninformed trader when they met and thus information asymmetry disappears or diminishes over time. However, when traders choose their own counterparty based on information precision, the informed traders do not want to be matched with uninformed traders. Information is shared only within each type, and the asymmetry between types increases after trades take place. Consequently, the informational inefficiency by allowing an over-the-counter market into the economy.

6 Discussion

Connection to Markets. I show that an over-the-counter market opens when the size of the centralized market is small, the asset values are closer to idiosyncratic than common, and private information of traders is less precise. Many financial derivatives such as forwards contracts, interest rate swaps, or equity or credit linked securities are traded in over-the-counter markets, even though their trading volumes (liquidity) are large. When these products are required to be held by traders until the maturity, it suggests that the purpose of trading can be hedging of traders' outside portfolios. This paper suggests that idiosyncratically valued assets tend to be traded in the over-the-counter markets. On the other hand, centralized markets attract assets traded mostly by speculators, such as stocks or bonds with short maturity, which are valued by future prices that are common to all traders. High-yield bonds that have low credit ranking are often traded in the over-the-counter markets (e.g., Hendershott and Madhavan (2015)). The volatile return prevents the traders' access to quality information and hence the information precision is low. This is consistent with this paper's prediction that low information precision encourages traders to choose over-the-counter markets.

Alternative Over-the-Counter Designs. I have endogenized centralized and over-the-counter markets assuming their prices and allocations based on an uniform-price double auction. This allows us to focus on the effects of the characteristics of market, asset, or traders, rather than the difference between mechanisms. With random matching, searching with frictions, or other mechanisms in literature introduced in over-the-counter markets, the effects in this paper continue to be present. For instance, suppose that the over-the-counter market is operated by random matching instead of traders' counterparty choice. Traders' expected utilities in the over-the-counter market would strengthen the effect of the asymmetric interdependence of traders' asset values and heterogeneous information precisions. Uninformed traders have a chance to meet an informed traders and to learn more precise information, while informed traders' liquidity can be improved with a higher chance of meeting uninformed counterparty. Introducing random matching mechanism in the over-the-counter market does not affect the endogenous market structure qualitatively, but it can increase traders' incentive to enter the over-the-counter market when the heterogeneity across traders is present. Exogenous frictions in the over-the-counter markets - a probability that a trader does not trade, cost of waiting, etc. - can decrease traders' incentive to trade in over-the-counter markets.

In this paper, traders' individual market choice occurs ex-ante, in that traders choose where to trade before their private information is realized. This model is appropriate when traders' individual asset values θ_i contains future returns of the asset in the markets and/or future returns of traders' individual portfolios, as interpreted in Section 2. The future returns from certain assets are often unobservable or costly to observe to those who are not in the market in order to keep market participants privacy. If the traders asset values or their private information are interdependent by other sources - for example, traders' endowments before markets, pre-trades, macroeconomic information, cheap talk, etc. - the model may incorporate *interim* market choice, in that, traders choose a market to participate in after they observe the private information. Interim market choice increases the dimension of heterogeneity, in addition to the correlation structure and information precision. A trader whose realized signal is high can be more attracted to the over-the-counter market since the difference between asset values and price, $|E[\theta_i|s_i, p] - p|$, is larger in a bilateral trades. [14] The additional heterogeneity of realized private information with interim market choice influence equilibrium distribution of traders' types in each market and the distribution of equilibrium prices, but the trade-off between learning and liquidity for each trader continues to shape trader's incentives.

[14]Boyarchenko, Lucca, and Veldkamp (2015) study the effect of realized private signals in market structure in a different market mechanism from this paper. They consider an inter-dealer market and dealer-customer market. Traders face a choice to be either a dealer or a customer. They show that traders who have a high private signal choose to trade directly in the inter-dealer market to keep their information private. Although the conjecture on the interim market choice in my model is related to the intuitions in Boyarchenko, Lucca, and Veldkamp (2015), the determinants for main results are different. In their paper, traders reveal their private information truthfully to the dealers, and thus, there is no learning incentive in over-the-counter markets. This paper considers traders' learning on the values due to demand schedule conditioning on equilibrium prices.

References

Acharya, V. and A. Bisin (2010): "Centralized versus Over-The-Counter Markets," working paper.

Atakan, A. and M. Ekmekci (2016): "Market Selection and the Information Content of Prices," working paper.

Atkeson, A., A. Eisfeldt, and P. Weill (2014): "Entry and Exit in OTC Derivatives Markets," working paper.

Attanasi, G., S. Centorrino, and I. Moscati (2016): "Over-the-counter Markets vs. Double Auctions: A Comparative Experimental Study," Journal of Behavioral and Experimental Economics, 63, 22-35.

Babus, A. and T. Hu (2016): "Endogenous Intermediation in Over-the-Counter Markets " working paper.

Babus, A. and P. Kondor (2016): "Trading and Information Diffusion in Over-The-Counter Markets," working paper.

Babus, A. and C. Parlatore (2017): "Strategic Fragmented Markets," working paper.

Back, K., R. Liu, and A. Teguia(2016): "Signaling in Over-the-Counter Markets: Benefits and Costs of Transparency," working paper.

Barclay, M., T. Hendershott, and D. T. McCormick (2003): "Competition among Trading Venues: Information and Trading on Electronic Communications Networks," Journal of Finance, 58, 6, 2637-2665.

Bessembinder, H. and H. Kaufman (1997): "A Comparison of Trade Execution Costs for NYSE and NASDAQ-Listed Stocks," Journal of Financial and Quantitative Analysis, 32, 3, 287-310.

Biais, B. and R. Green (2007): "The Microstructure of the Bond Market in the 20th Century," working paper.

Bolton, P., T. Santos, and J. Scheinkman (2015): "Cream Skimming in Financial Markets," working paper.

Bessembinder H. and K. Venkataraman (2014): "Does an Electronic Stock Exchange Need an Upstairs Markets?" Journal of Financial Economics, 73, 1, 3-36.

Chang, B. and S. Zhang (2016): "Endogenous Market Making and Network Formation," working paper.

Conrad, J., K. Johnson, and S. Wahal (2003): "Institutional trading and alternative trading systems," Journal of Financial Economics, 70, 1, 99-134.

Degryse, H., F. Jong, and V. Kervel (2015): "The Impact of Dark Trading and Visible Fragmentation on Market Quality," Review of Finance, 19, 4, 1587-1622.

Duffie, D., L. Qiao, and Y. Sun (2017): "Dynamic Directed Random Matching," working paper.

Duffie, D., N. Gârleanu, and L.H. Pedersen (2005): "Over-the-Counter Markets," Econometrica, 73, 6, 1815-1847.

Duffie, D., S. Malamud, and G. Manso (2014): "Information Percolation in Segmented Markets," Journal of Economic Theory, 153, 1-32.

Duffie, D. and C. Wang (2016): “Efficient Contracting in Network Financial Markets,” working paper.
Farboodi, M. (2015): “Intermediation and Voluntary Exposure to Counterparty Risk,” working paper.
Farboodi, M., G. Jarosch, and G. Menzio (2016): “Intermediation as Rent Extraction,” working paper.
Farboodi, M., G. Jarosch, and R. Shimer (2017): “The Emergence of Market Structure,” working paper.
Glode, V. and C. Opp (2017): “Can Decentralized Markets Be More Efficient?,” working paper.
Golosov, M., G. Lorenzoni, and A. Tsyvinski (2014): “Decentralized Trading with Private Information,” Econometrica, 82, 3, 1055-1091.
Hendershott, T. and A. Madhavan (2015): “Click or Call? Auction versus Search in the Over-the-Counter Market,” Journal of Finance, 70, 1, 419-447.
Hugonnier, J., B. Lester, and P. O. Weill (2016): “Heterogeneity in Decentralized Asset Markets,” working paper.
Kirilenko, A. (2000): “On the Endogeneity of Trading Arrangements,” Journal of Financial Markets, 3, 287-314.
Malamud, S. and M. Rostek (2014): “Decentralized Exchange,” working paper.
Maurin, V. (2015): “Liquidity Fluctuations in Over the Counter Markets,” working paper.
Praz, R. (2015): “Equilibrium Asset Pricing with Both Liquid and Illiquid Markets,” working paper.
Ready, M. (2014): “Determinants of Volume in Dark Pool Crossing Networks,” working paper.
Rostek, M. and M. Weretka (2012): “Price Inference in Small Markets,” Econometrica, 80, 2, 687-711.
Rostek, M. and J. H. Yoon (2017): “Inference Design,” working paper.
Vayanos, D. and T. Wang (2007): “A Search-Based Theory of the On-the-Run Phenomenon,” Journal of Finance, 63, 3, 1361-1398.
Vayanos, D. and P. O. Weill (2008): “Search and Endogenous Concentration of Liquidity in Asset Markets,” Journal of Economic Theory, 136, 66-104.
Viswanathan, S. and J. Wang (2002): “Market Architecture: Limit-Order Books versus Dealership Markets,” Journal of Financial Markets, 5, 127-167.
Vives, X. (2011): “Strategic Supply Function Competition with Private Information,” Econometrica, 79, 6, 1919-1966.
Vohra, R. and A. Peivandi (2017): “Instability of Centralized Markets,” working paper.
Wang, C. (2017): “Core-Periphery Trading Networks,” working paper.
Weill, P. O. (2008): “Liquidity Premia in Dynamic Bargaining Markets,” Journal of Economic Theory, 140, 1, 66-96.
Zong, Z. (2014): “The Risk Sharing Benefit versus the Collateral Cost: The Formation of the Inter-Dealer Network in Over-the-Counter Trading, ” working paper.
Zhu, H. (2012): “Finding a Good Price in Opaque Over-the-Counter Markets,” Review of Financiel Studies, 25, 4, 1255-1285.

A Proofs

Proof of Proposition 1 (Equilibrium Representation in a Market). For a given price impact $\lambda_i > 0$ and inference $E[\theta_i|s_i, p] = c_{\theta,i}E[\theta_i] + c_{s,i}s_i + c_{p,i}p$, trader i's first order condition gives his best response, i.e. demand schedule.

$$q_i = \frac{E[\theta_i|s_i,p] - p}{\mu Var(\theta_i|s_i,p) + \lambda_i} = \frac{c_{\theta,i}E[\theta_i] + c_{s,i}s_i - (1 - c_{p,i})p}{\mu Var(\theta_i|s_i,p) + \lambda_i}.$$

With positive price impacts, the second order condition holds for all i:

$$-\mu Var(\theta_i|s_i,p) - 2\lambda_i < 0.$$

The market clearing condition $\sum_i q_i(\cdot) = 0$ determines equilibrium price from the demand function.

$$p = (\sum_i \frac{1 - c_{p,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i})^{-1} \sum_i \frac{c_{\theta,i}E[\theta_i] + c_{s,i}s_i}{\mu Var(\theta_i|s_i,p) + \lambda_i}.$$

Since the price is a linear function of traders' private information $\{s_i\}_i$, it follows a normal distribution as well as the signals. This Gaussian-linear structure allows us to use the Projection Theorem in order to derive traders' conditional expectation on asset value. First, the unconditional expectation of price is equal to $E[\theta_i]$ which is same across traders. It results in $c_{\theta,i} + c_{s,i} + c_{p,i} = 1$ for any i. The inference coefficient $\{c_{s,i}, c_{p,i}\}$ is

$$\begin{bmatrix} c_{s,i} \\ c_{p,i} \end{bmatrix} = \begin{bmatrix} Var(s_i) & Cov(s_i,p) \\ Cov(s_i,p) & Var(p) \end{bmatrix}^{-1} \begin{bmatrix} Cov(\theta_i,s_i) \\ Cov(\theta_i,p) \end{bmatrix}, \tag{7}$$

and the conditional variance of θ_i over (s_i, p) is

$$\begin{aligned} Var(\theta_i|s_i,p) &= Var(\theta_i) - \begin{bmatrix} Cov(\theta_i,s_i) \\ Cov(\theta_i,p) \end{bmatrix} \cdot \begin{bmatrix} Var(s_i) & Cov(s_i,p) \\ Cov(s_i,p) & Var(p) \end{bmatrix}^{-1} \begin{bmatrix} Cov(\theta_i,s_i) \\ Cov(\theta_i,p) \end{bmatrix} \\ &= Var(\theta_i) - (Cov(\theta_i,s_i)c_{s,i} + Cov(\theta_i,p)c_{p,i}). \end{aligned}$$

We denote $\sigma_i^2 = \sigma_{i,\varepsilon}^2/\sigma_\theta^2$, the relative variance of noise in private information compared to variance of asset values. By plugging the following variance and covariance of (s_i, p) into equation (7),

$$Var(p) = (\sum_i \frac{1 - c_{p,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i})^{-2} \Big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i}\Big)_i \cdot (\sigma_\theta^2 \Sigma + diag(\sigma_{i,\varepsilon}^2)_i) \Big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i}\Big)_i,$$

$$Cov(s_i,p) = (\sum_i \frac{1 - c_{p,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i})^{-1} \Big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p) + \lambda_i}\Big)_i \cdot \Big(\sigma_\theta^2 \rho_{ij} + \sigma_{i,\varepsilon}^2 \mathbf{1}_{j=i}\Big)_j,$$

we get a fixed point problem for the inference coefficients $\{c_{s,i}, c_{p,i}\}_i$,

$$c_{s,i} = \frac{\sum_{j,k} \frac{c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})-c_{s,j}c_{s,k}\rho_{ij}(\rho_{ik}+\sigma_i^2\mathbf{1}_{i=k})}{(\mu Var(\theta_j|s_j,p)+\lambda_j)(\mu Var(\theta_k|s_k,p)+\lambda_k)}}{\sum_{j,k}\frac{(1+\sigma_i^2)c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})-c_{s,j}c_{s,k}(\rho_{ij}+\sigma_i^2\mathbf{1}_{i=j})(\rho_{ik}+\sigma_i^2\mathbf{1}_{i=k})}{(\mu Var(\theta_j|s_j,p)+\lambda_j)(\mu Var(\theta_k|s_k,p)+\lambda_k)}}, \quad \forall i, \tag{8}$$

$$c_{p,i} = \frac{\sum_i \frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\sum_j \frac{(1+\sigma_i^2)c_{s,j}\rho_{ij}-c_{s,j}(\rho_{ij}+\sigma_i^2\mathbf{1}_{i=j})}{\mu Var(\theta_j|s_j,p)+\lambda_j}}{\sum_{j,k}\frac{(1+\sigma_i^2)c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})-c_{s,j}c_{s,k}(\rho_{ij}+\sigma_i^2\mathbf{1}_{i=j})(\rho_{ik}+\sigma_i^2\mathbf{1}_{i=k})}{(\mu Var(\theta_j|s_j,p)+\lambda_j)(\mu Var(\theta_k|s_k,p)+\lambda_k)}} \quad \forall i. \tag{9}$$

In addition, the price impacts are characterized by

$$\lambda_i = \Big(\sum_{j\neq i}\frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\Big)^{-1}, \quad \forall i, \tag{10}$$

for a given inference coefficients $\{c_{p,j}\}_j$ and the conditional variance of asset values,

$$Var(\theta_i|s_i,p) = \sigma_\theta^2\Big(1-c_{s,i}-c_{p,i}(\sum_j \frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^{-1}\sum_j \frac{c_{s,j}\rho_{ij}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\Big), \quad \forall i. \tag{11}$$

Equations (8) - (11) solves $\{c_{s,i}, c_{p,i}, \lambda_i, Var(\theta_i|s_i,p)\}_i$, and thus, characterizes equilibrium.

With the equilibrium characterization, a trader's indirect interim utility is

$$\begin{aligned} E[u_i|s_i,p] &= -\exp\Big(-\mu(-pq_i + E[\theta_i|s_i,p]q_i - \frac{\mu}{2}Var(\theta|s_i,p)q_i^2)\Big) \\ &= -\exp\Big(-\mu(\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}(E[\theta_i|s_i,p]-p)^2)\Big), \end{aligned}$$

while his ex-ante utility is

$$E[u_i] = E\Big[-\exp\Big(-\mu(\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}(E[\theta_i|s_i,p]-p)^2)\Big)\Big].$$

Considering that the difference of individual expected asset value from equilibrium price, $(E[\theta_i|s_i,p]-p)$, follows a normal distribution that is generated by Gaussian structure of $\{\theta_i, s_i\}_i$, the expectation on the right hand side of the above equation is in form of the moment generating function for χ_k^2 distribution. It provides an explicit formula for the ex-ante indirect utility:

$$\begin{aligned}
E[E[u_i|s_i,p]] &= E\Big[-\exp\Big(-\mu\big(\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}(E[\theta_i|s_i,p]-p)^2\big)\Big)\Big] \\
&= E\Big[-\exp\Big(-\mu\big(\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p)\chi^2_{k=1}\Big)\Big] \\
&= -\Big(1-2\Big\{-\mu\big(\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p)\big)\Big\}\Big)^{-1/2} \\
&= -\Big(1+2\mu\frac{\mu Var(\theta|s_i,p)+2\lambda_i}{2(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p)\Big)^{-1/2}
\end{aligned}$$

We introduce a measure for the ex-ante utility. For each i,

$$\tau_i \equiv \big(\frac{1}{E[u_i]^2}-1\big) = \frac{\mu(\mu Var(\theta|s_i,p)+2\lambda_i)}{(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p).$$

The ex-ante utility is strictly increasing and strictly concave in τ_i. ■

Proof of Proposition 2 (Benefits of Learning and Liquidity). In equilibrium for a given market, subject to existence, the ex-ante indirect utility of a trader i is strictly increasing and strictly concave in the following measure:

$$\xi_i = \frac{\mu(\mu Var(\theta|s_i,p)+2\lambda_i)}{(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p) = \frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)}.$$

Intuitively, more negative asset correlation increases the variance of difference between individual asset value and price, $Var(E[\theta_i|s_i,p]-p)$; the higher information precision of other traders, on average, improves trader i's learning from price so that decreases $Var(\theta_i|s_i,p)$; and the larger market size decreases price impact λ_i. Suppose that the correlation of traders' asset values and information precision is symmetric across traders: when the average correlation is defined by $\bar{\rho}_i \equiv \big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\big)^{-1}\frac{1}{I-1}\sum_{j\neq i}\frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\rho_{ij}$ for each i and $\sigma_i^2 = \sigma_{i,\varepsilon}^2/\sigma_\theta^2$ for each i, the symmetric market assumes $\bar{\rho}_i = \bar{\rho}$ and $\sigma_i^2 = \sigma^2$ for all i. In general, the inference coefficients are

$$\begin{aligned}
c_{s,i} &= \frac{\frac{1}{I-1}\sum_{j\neq i}\big(\frac{c_{s,j}}{(\mu Var(\theta_j|s_j,p)+\lambda_j)}\big)^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - \big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\big)^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)}{(1+\sigma_i^2)\frac{1}{I-1}\sum_{j\neq i}\big(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\big)^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - \big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\big)^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)}, \\
c_{p,i} &= \frac{\big(\frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}+\frac{1}{\lambda_i}\big)\ \frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\bar{\rho}_i\sigma_i^2}{(1+\sigma_i^2)\frac{1}{I-1}\sum_{j\neq i}\big(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\big)^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - \big(\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\big)^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)}.
\end{aligned}$$

In symmetric markets, for each i,

$$c_{s,i} = \frac{1-\bar{\rho}}{1+\sigma_i^2-\bar{\rho}}, \qquad c_{p,i} = \frac{I\bar{\rho}\sigma^2}{(1-\bar{\rho})(1+\sigma^2+(I-1)\bar{\rho})+\bar{\rho}\sigma^2},$$
$$\lambda_i = \Big(\sum_{j\neq i}\frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\Big)^{-1} = \frac{\mu Var(\theta_i|s_i,p)}{I-2}.$$

Furthermore, the inference coefficients characterize the learning effect in expected utility.

$$\begin{aligned}
& Var(E[\theta_i|s_i,p]-p) = \big(c_{s,i}^2\sigma_\theta^2(1+\sigma_i^2)+(1-c_{p,i})^2 Var(p) - 2c_{s,i}(1-c_{p,i})Cov(s_i,p)\big)\\
= \;& \sigma_\theta^2\big(c_{s,i}^2(1+\sigma_i^2)+(1-c_{p,i})^2(\sum_i\frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-2}\sum_{j,k}\frac{c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})}{(\mu Var(\theta_j|s_i,p)+\lambda_j)(\mu Var(\theta_j|s_i,p)+\lambda_j)}\\
& -2c_{s,i}(1-c_{p,i})(\sum_i\frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-1}\sum_j\frac{c_{s,j}(\rho_{ij}+\sigma_i^2\mathbf{1}_{j=i})}{\mu Var(\theta_j|s_j,p)+\lambda_j}\big).
\end{aligned}$$

$$\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)} = \frac{\left(\begin{array}{c} c_{s,i}^2(1+\sigma_i^2)+(1-c_{p,i})^2(\sum_i\frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-2}\sum_{j,k}\frac{c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})}{(\mu Var(\theta_j|s_i,p)+\lambda_j)(\mu Var(\theta_j|s_i,p)+\lambda_j)}\\ -2c_{s,i}(1-c_{p,i})(\sum_i\frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-1}\sum_j\frac{c_{s,j}(\rho_{ij}+\sigma_i^2\mathbf{1}_{j=i})}{\mu Var(\theta_j|s_j,p)+\lambda_j}\end{array}\right)}{1-c_{s,i}-c_{p,i}(\sum_j\frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^{-1}\sum_j\frac{c_{s,j}\rho_{ij}}{\mu Var(\theta_j|s_j,p)+\lambda_j}}.$$

In symmetric market, these equations are simplified into

$$Var(E[\theta_i|s_i,p]-p) = \sigma_\theta^2 c_s^2\frac{I-1}{I}(1+\sigma^2-\bar{\rho}).$$

The above characterization for the symmetric markets provides the following comparative statics of the three characteristics (i) the market size, (ii) the average correlation $\bar{\rho}_i$, and (iii) information precision $\phi_i = 1/\sigma^2$: The liquidity effect on utility is captured by the term $\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2}$. With this closed-form solution of inference parameters and price impact,

$$\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2} = 1-(\frac{\widehat{\lambda}_i}{1+\widehat{\lambda}_i})^2 = 1-\Big(\frac{(1+\sigma^2-\bar{\rho})(1+(I-1)\bar{\rho})}{(I-1)(1-\bar{\rho})(1+\sigma^2+(I-1)\bar{\rho})}\Big)^2.$$

The liquidity term increases as I increases or $\bar{\rho}$ decreases.

$$\frac{\partial}{\partial I}\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2} = 2\frac{\widehat{\lambda}_i}{1+\widehat{\lambda}_i}\frac{1+\sigma^2-\bar{\rho}}{1-\bar{\rho}}\frac{\sigma^2+(1+(I-1)\bar{\rho})^2}{(I-1)^2(1+\sigma^2+(I-1)\bar{\rho})^2} > 0$$

Larger market size and/or more negative correlation with others on average results in more liquidity, and thus higher utility for traders. When the information precision $\phi = 1/\sigma^2$ increases, the endogenous liquidity of the market increases if $\bar{\rho} > 0$, and decreases if $\bar{\rho} < 0$.

$$\frac{\partial}{\partial \sigma^2}\frac{1+2\widehat{\lambda}_i}{(1+\widehat{\lambda}_i)^2} = -2\frac{\widehat{\lambda}_i}{1+\widehat{\lambda}_i}\frac{(1+(I-1)\bar{\rho})}{(I-1)(1-\bar{\rho})}\frac{I\bar{\rho}}{(1+\sigma^2+(I-1)\bar{\rho})^2}.$$

The effect of learning from the price on utility is measured by

$$\frac{Var(E[\tilde{\theta}_i|s_i,p]-p)}{Var(\tilde{\theta}_i|s_i,p)} = \frac{I-1}{I}\frac{(1-\bar{\rho})^2(1+\sigma^2+(I-1)\bar{\rho})}{\sigma^2(\sigma^2+(1-\bar{\rho})(1+(I-1)\bar{\rho}))},$$

which is increasing in information precision $\phi = 1/\sigma^2$. The effect of average correlation $\bar{\rho}$ is ambiguous. The utility component due to learning is decreasing with respect to $\bar{\rho}$, if and only if, $(1+\sigma^2)+(2I-3)(1+\sigma^2)\bar{\rho}+(I-3)(I-1)\bar{\rho}^2-(I-1)^2\bar{\rho}^3 > 0$.

In asymmetric markets, we can heuristically explore influences of the three characteristics on trader i's expected utility $E[u_i]$. We impose another simplicity on information precision: $\sigma_j^2 = \sigma_{-i}^2$ for any $j \neq i$. It implies that all other traders $j \neq i$ except for trader i have symmetric strategy. This assumption is to make the derivation simpler, but it does not affect conclusions.

$$\widehat{\lambda}_i = \frac{1}{(I-1)(1-c_{p,-i})}\frac{\mu Var(\theta_{-i}|s_{-i},p)+\lambda_{-i}}{\mu Var(\theta_i|s_i,p)}$$

$$c_{s,i} = \frac{1-\bar{\rho}_i}{1+\sigma_i^2-\bar{\rho}_i}, \qquad c_{p,i} = \frac{\bar{\rho}_i\sigma_i^2}{(1-\bar{\rho}_i)(1+\sigma_i^2+(I-1)\bar{\rho}_i)+\bar{\rho}_i\sigma_i^2}\frac{1+2\widehat{\lambda}_i}{\widehat{\lambda}_i}.$$

$$\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)} = \frac{c_{s,i}^2 Var(s_i)+(1-c_{p,i})^2 Var(p)-2c_{s,i}(1-c_{p,i})Cov(s_i,p)}{1-c_{s,i}-c_{p,i}(\sum_j \frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^{-1}\sum_j \frac{c_{s,j}\rho_{ij}}{\mu Var(\theta_j|s_j,p)+\lambda_j}}. \tag{12}$$

(i) Market size, equivalently, the number of traders I: Suppose that $\bar{\rho}_i$ and σ_i^2 are fixed. We can see that I affects utility only through the normalized price impact $\widehat{\lambda}_i$ and the inference coefficient on price $c_{p,i}$. As I increases, $\widehat{\lambda}_i$ decreases and $|c_{p,i}|$ increases for sufficiently large I. The liquidity effect in utility, $(1+2\widehat{\lambda}_i)/(1+\widehat{\lambda}_i)^2$, increases by the decrease of $\widehat{\lambda}_i$. The learning effect in equation (12) increases when $\bar{\rho}_i > 0$ and decreases when $\bar{\rho}_i < 0$. With sufficiently symmetric market, the effect of liquidity dominates the learning effect, so that the expected utility $E[u_i]$ increases in the market size I.

(ii) Average correlation $\bar{\rho}_i = \bar{\rho}$: As more negative correlation $\bar{\rho}_i$, i.e., as $\bar{\rho}_i$ decreases, the inference coefficient on private information $c_{s,i}$ decreases and the absolute value of the coefficient on price $|c_{p,i}|$ increases:

$$\frac{\partial c_{p,i}}{\partial \bar{\rho}_i} = \frac{\sigma_i^2(1+\sigma_i^2+(I-1)\bar{\rho}_i^2)}{((1-\bar{\rho}_i)(1+\sigma_i^2+(I-1)\bar{\rho}_i)+\bar{\rho}_i\sigma_i^2)^2}\frac{1+2\widehat{\lambda}_i}{\widehat{\lambda}_i} > 0.$$

It implies that the price impact $\widehat{\lambda}_i$ and the conditional variance $Var(\theta_i|s_i,p)$ both decrease. In addition, it increases $Var(E[\theta_i|s_i,p]-p)$ by decreasing $Cov(s_i,p)$. Hence, the more negative correlation $\bar{\rho}$ increases both liquidity and learning effects and thus increases traders' expected utility.

(iii) Information precision σ^2_{-i} of other traders: as the information precision $1/\sigma^2_{-i}$ increases (i.e., σ^2_{-i} decreases), trader $j \neq i$'s inference coefficient on private information $c_{s,-i}$ increases and the absolute value of the coefficient on price $|c_{p,-i}|$ decreases.

$$\frac{\partial c_{p,-i}}{\partial \sigma^2_{-i}} = \frac{\bar{\rho}(1-\bar{\rho})(1+(I-1)\bar{\rho})}{((1-\bar{\rho})(1+\sigma^2_{-i}+(I-1)\bar{\rho})+\bar{\rho}\sigma^2_{-i})^2}\frac{1+2\widehat{\lambda}_{-i}}{\widehat{\lambda}_{-i}}.$$

It makes $\widehat{\lambda}_i$ decreasing if $\bar{\rho}_{-i}>0$ and increasing $\widehat{\lambda}_i$ otherwise. Hence, the liquidity effect of trader i's utility changes depending on the correlation of other traders: as σ^2_{-i} decreases, the liquidity effect $(1+2\widehat{\lambda}_i)/(1+\widehat{\lambda}_i)^2$ increases when $\bar{\rho}_{-i}>0$ and decreases when $\bar{\rho}_{-i}>0$. The learning effect in trader i's utility is increasing in other traders' information precision by the decrease of $Var(\theta_i|s_i,p)$. The liquidity and learning can create a trade-off with respect to others' information precision. ■

Proof of Theorem 1 (Endogenous Market Structure). This proof is under the condition that equilibrium exists. Suppose that only a centralized market opens in equilibrium but no over-the-counter market does. Since no trader has an incentive to switch his market choice to the over-the-counter market, his expected utilities $E[u_i^{CM};\text{all in CM}]$, when all traders are in the centralized market, is higher than a potential utility in the over-the-counter market. The potential utility in the over-the-counter market $E[u_i;OTC(i,j)]$ is pair-specific, i.e., it depends on the pair (i,j). A sufficient and necessary condition on the endogenous market structure consists of only the centralized market is that there is no trader who has a positive incentive to deviate to the over-the-counter market with his best counterparty. This condition is equivalent to that the utility in centralized market is higher than the maximum utility trader i would get in over-the-counter market:

$$E[u_i^{CM};\text{all in CM}] > \max_{j\neq i} E[u_i;OTC(i,j)], \quad \forall i.$$

Under the symmetry assumption, $\frac{1}{I-1}\sum_{j\neq i}\rho_{ij}=\bar{\rho}$ and $\phi_i=\phi=1/\sigma^2_\varepsilon$ for all i, the equilibrium utility in each market is characterized as follows. Suppose that $\sigma=\sigma_\varepsilon/\sigma_\theta$. In the centralized market,

$$c_s = \frac{1-\bar{\rho}}{1+\sigma^2-\bar{\rho}}, \qquad c_p = \frac{I(1-c_p)\bar{\rho}\sigma^2}{(1-\bar{\rho})(1+\sigma^2+(I-1)\bar{\rho})} = \frac{I\bar{\rho}\sigma^2}{(1+\sigma^2-\bar{\rho})(1+(I-1)\bar{\rho})},$$

$$\widehat{\lambda}_i = \frac{\lambda_i}{\mu Var(\tilde{\theta}_i|s_i,p)} = \frac{(1+(I-1)\bar{\rho})(1+\sigma^2-\bar{\rho})}{(I-2)(1+\sigma^2)+((I-1)^2+1-2(I-1)(1+\sigma^2))\bar{\rho}-(I-1)(I-2)\bar{\rho}^2},$$

$$Var(\tilde{\theta}_i|s_i,p) = \frac{(1+\sigma^2)+(I-2)\bar{\rho}-(I-1)\bar{\rho}^2}{(1+\sigma^2+(I-1)\bar{\rho})(1+\sigma^2-\bar{\rho})}\sigma_\varepsilon^2; \quad Var(E[\tilde{\theta}_i|s_i,p]-p) = \frac{(1-\bar{\rho})^2}{1+\sigma^2-\bar{\rho}}\frac{I-1}{I}\sigma_\theta^2.$$

From these equilibrium variables, the equilibrium utility is characterized by

$$\xi_i^{cm} \equiv \big(\frac{1}{E[u_i]^2}-1\big) = \frac{(I-1)^2(1-\bar{\rho})^2(1+\sigma^2+(I-1)\bar{\rho})^2-(1+\sigma^2-\bar{\rho})^2(1+(I-1)\bar{\rho})^2}{(I-1)I\sigma^2(1+\sigma^2+(I-1)\bar{\rho})((1+\sigma^2)+(I-2)\bar{\rho}-(I-1)\bar{\rho}^2)}.$$

On the other hand, the over-the-counter market provides the equilibrium characterization with the following endogenous parameters:

$$c_s = \frac{1-\rho_{ij}}{1+\sigma^2-\rho_{ij}}, \qquad c_p = \frac{I(1-c_p)\rho_{ij}\sigma^2}{(1-\rho_{ij})(1+\sigma^2+\rho_{ij})} = \frac{2\rho_{ij}\sigma^2}{(1+\sigma^2-\rho_{ij})(1+\rho_{ij})},$$

$$\widehat{\lambda}_i = \frac{\lambda_i}{\mu Var(\tilde{\theta}_i|s_i,p)} = \frac{(1+\rho_{ij})(1+\sigma^2-\rho_{ij})}{-2\sigma^2\rho_{ij}},$$

$$Var(\tilde{\theta}_i|s_i,p) = \frac{1+\sigma^2-\rho_{ij}^2}{(1+\sigma^2)^2-\rho_{ij}^2}\sigma_\varepsilon^2; \quad Var(E[\tilde{\theta}_i|s_i,p]-p) = \frac{(1-\rho_{ij})^2}{1+\sigma^2-\rho_{ij}}\frac{1}{2}\sigma_\theta^2.$$

From these equilibrium variables, the equilibrium utility is characterized by

$$\xi_i^{otc} \equiv \big(\frac{1}{E[u_i]^2}-1\big) = \frac{(1-\rho_{ij})^2(1+\sigma^2+\rho_{ij})^2-(1+\sigma^2-\rho_{ij})^2(1+\rho_{ij})^2}{2\sigma^2(1+\sigma^2+\rho_{ij})(1+\sigma^2-\rho_{ij}^2)}.$$

Comparing the equilibrium utility in two markets,

$$\xi_i^{CM} > \xi_i^{OTC} \quad \Leftrightarrow \quad \frac{1+2\widehat{\lambda}_i^{cm}}{(1+\widehat{\lambda}_i^{cm})^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p_{cm})} > \frac{1+2\widehat{\lambda}_i^{otc}}{(1+\widehat{\lambda}_i^{otc})^2}\frac{Var(E[\theta_i|s_i,s_j]-p)}{Var(\theta|s_i,s_j)}.$$

$$\frac{(I-1)^2(1-\bar{\rho})^2(1+\sigma^2+(I-1)\bar{\rho})^2-(1+\sigma^2-\bar{\rho})^2(1+(I-1)\bar{\rho})^2}{(I-1)I(1+\sigma^2+(I-1)\bar{\rho})((1+\sigma^2)+(I-2)\bar{\rho}-(I-1)\bar{\rho}^2)} > \frac{(1-\rho_{ij})^2(1+\sigma^2+\rho_{ij})^2-(1+\sigma^2-\rho_{ij})^2(\ldots}{2(1+\sigma^2+\rho_{ij})(1+\sigma^2-\rho_{ij}^2)}$$

Here, without loss of generality, the correlations between asset values $(\tilde{\theta}_i)_i$ can be written by $\bar{\rho} = \frac{\sigma_{cv}^2}{\sigma_{cv}^2+\sigma_{iv}^2}$ and $\rho_{ij} = \min_{j\neq i} Corr(\tilde{\theta}_i,\tilde{\theta}_j) = 2\bar{\rho}-1 = \frac{\sigma_{cv}^2-\sigma_{iv}^2}{\sigma_{cv}^2+\sigma_{iv}^2}$.

$$\frac{(I-1)^2(1-\bar{\rho})^2(\sigma^2+1+(I-1)\bar{\rho})^2-(\sigma^2+1-\bar{\rho})^2(1+(I-1)\bar{\rho})^2}{(I-1)I(\sigma^2+1+(I-1)\bar{\rho})(\sigma^2+(1-\bar{\rho})(1+(I-1)\bar{\rho}))} > \frac{(2(1-\bar{\rho}))^2(\sigma^2+2\bar{\rho})^2-(\sigma^2+2(1-\bar{\rho}))^2(2\bar{\rho}\ldots}{2(\sigma^2+2\bar{\rho})(\sigma^2+2\bar{\rho}\cdot 2(1-\bar{\rho}))} \tag{13}$$

The inequality can be rewritten as

$$1-\bar{\rho} < \frac{K+\sqrt{K^2+(I^2-1)(\sigma^2+z)^2(\sigma^2+y)^2+2y^2(\sigma^2+z)^2-(4I(I-1)(\sigma^2+y)^2z^2)L}}{(I^2-1)(\sigma^2+z)^2(\sigma^2+y)^2+2y^2(\sigma^2+z)^2-(4I(I-1)(\sigma^2+y)^2z^2)}\sigma^2 \equiv \hat{\kappa}(\sigma^2),$$

where $K = ((I-1)Iz^2(\sigma^2+y)^2-(\sigma^2+z)^2y^2) > 0, L = ((I-1)Iz^2(\sigma^2+y)^2-2(\sigma^2+z)^2y^2) > 0$, $y = 1+(I-1)\bar{\rho} > 0$, and $z = 2\bar{\rho} < 1$. It shows that the sufficient and necessary condition on

$E[u_i^{CM}; \text{all in CM}] > \max_{j\neq i} E[u_i; OTC(i,j)]$ is

$$\frac{\sigma_{iv}^2}{\sigma_{cv}^2+\sigma_{iv}^2} = 1-\bar{\rho} < \hat{\kappa}(\sigma^2).$$

In addition, the inequality (13) can be also written in terms of signal variance $\sigma^2 = \frac{\sigma_\varepsilon^2}{\sigma_{cv}^2+\sigma_{iv}^2}$:

$$\sigma^2 < \frac{-2K+\sqrt{2K^2+L(I^2-1)(\sigma^2+z)^2(\sigma^2+y)^2+2y^2(\sigma^2+z)^2-(4I(I-1)(\sigma^2+y)^2z^2)}}{((I-1)Iz^2(\sigma^2+y)^2-2(\sigma^2+z)^2y^2)} \equiv \frac{1}{\hat{\phi}(\sigma_{cv}^2+\sigma_{iv}^2)}$$

Hence, traders choose the centralized market if and only if the information precision satisfies

$$\phi_i = \frac{1}{\sigma_\varepsilon^2} = \frac{\sigma_{cv}^2+\sigma_{iv}^2}{\sigma^2} > \hat{\phi}(\sigma_{cv}^2, \sigma_{iv}^2, \Sigma).$$

The over-the-counter market is chosen by a trader if these inequalities are violated, i.e., $\frac{\sigma_{iv}^2}{\sigma_{cv}^2+\sigma_{iv}^2} > \hat{\kappa}(\sigma^2)$ and $\phi_i < \hat{\phi}(\sigma_{cv}^2, \sigma_{iv}^2, \Sigma)$. The proof is complete for symmetric markets.

With asymmetric traders, the equilibrium utility in each market is characterized as follows. In the centralized market:

$$\begin{aligned}
c_{s,i} &= \frac{\frac{1}{I-1}\sum_{j\neq i}(\frac{c_{s,j}}{(\mu Var(\theta_j|s_j,p)+\lambda_j)})^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)}{(1+\sigma_i^2)\frac{1}{I-1}\sum_{j\neq i}(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)},\\
c_{p,i} &= \frac{(\frac{1}{I-1}\sum_j \frac{1}{\lambda_j})\ \frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}\bar{\rho}_i\sigma_i^2}{(1+\sigma_i^2)\frac{1}{I-1}\sum_{j\neq i}(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^2(1+\sigma_j^2+(I-1)\bar{\rho}_j) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^2\bar{\rho}_i(1+\sigma_i^2+(I-1)\bar{\rho}_i)}.
\end{aligned}$$

$$\begin{aligned}
& Var(E[\theta_i|s_i,p]-p) = \big(c_{s,i}^2\sigma_\theta^2(1+\sigma_i^2)+(1-c_{p,i})^2Var(p)-2c_{s,i}(1-c_{p,i})Cov(s_i,p)\big)\\
= \; & \sigma_\theta^2\big(c_{s,i}^2(1+\sigma_i^2)+(1-c_{p,i})^2(\sum_i \frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-2}\sum_{j,k}\frac{c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})}{(\mu Var(\theta_j|s_i,p)+\lambda_j)(\mu Var(\theta_j|s_i,p)+\lambda_j)}\\
& -2c_{s,i}(1-c_{p,i})(\sum_i \frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-1}\sum_j \frac{c_{s,j}(\rho_{ij}+\sigma_i^2\mathbf{1}_{j=i})}{\mu Var(\theta_j|s_j,p)+\lambda_j}\big)
\end{aligned}$$

$$\lambda_i = \Big(\sum_{j\neq i}\frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\Big)^{-1}.$$

$$Var(\theta_i|s_i,p) = \sigma_\theta^2\Big(1-c_{s,i}-c_{p,i}(\sum_j \frac{1-c_{p,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j})^{-1}\sum_j\frac{c_{s,j}\rho_{ij}}{\mu Var(\theta_j|s_j,p)+\lambda_j}\Big).$$

$$\xi_i^{cm} \equiv (\frac{1}{E[u_i]^2}-1) = \frac{\mu(\mu Var(\theta|s_i,p)+2\lambda_i)}{(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p).$$

On the other hand, the over-the-counter market provides the equilibrium characterization with the following endogenous parameters:

$$c_{s,i} = \frac{(\frac{c_{s,j}}{(\mu Var(\theta_j|s_j,s_i)+\lambda_j)})^2(1+\sigma_j^2+\rho) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,s_j)+\lambda_i})^2\rho(1+\sigma_i^2+\rho)}{(1+\sigma_i^2)(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,s_i)+\lambda_j})^2(1+\sigma_j^2+\rho) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,s_j)+\lambda_i})^2\rho(1+\sigma_i^2+\rho)},$$

$$c_{p,i} = \frac{(\frac{1}{\lambda_j}+\frac{1}{\lambda_i})\ \frac{c_{s,i}}{\mu Var(\theta_i|s_i,s_j)+\lambda_i}\rho\sigma_i^2}{(1+\sigma_i^2)(\frac{c_{s,j}}{\mu Var(\theta_j|s_j,s_i)+\lambda_j})^2(1+\sigma_j^2+\rho) - (\frac{c_{s,i}}{\mu Var(\theta_i|s_i,s_j)+\lambda_i})^2\rho(1+\sigma_i^2+\rho)}.$$

$$\begin{aligned}
& Var(E[\theta_i|s_i,p]-p) = \big(c_{s,i}^2\sigma_\theta^2(1+\sigma_i^2) + (1-c_{p,i})^2 Var(p) - 2c_{s,i}(1-c_{p,i})Cov(s_i,p)\big) \\
= \; & \sigma_\theta^2\big(c_{s,i}^2(1+\sigma_i^2) + (1-c_{p,i})^2(\sum_i \frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-2}\sum_{j,k}\frac{c_{s,j}c_{s,k}(\rho_{jk}+\sigma_j^2\mathbf{1}_{j=k})}{(\mu Var(\theta_j|s_i,p)+\lambda_j)(\mu Var(\theta_k|s_k,p)+\lambda_k)} \\
& -2c_{s,i}(1-c_{p,i})(\sum_i \frac{1-c_{p,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i})^{-1}\sum_j \frac{c_{s,j}(\rho_{ij}+\sigma_i^2\mathbf{1}_{j=i})}{\mu Var(\theta_j|s_j,p)+\lambda_j}\big) \\
& Var(E[\theta_i|s_i,s_j]-p) = Var\Big(\frac{(1+\sigma_j^2-\rho^2)s_i+\rho\sigma_i^2 s_j}{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2} - p\Big)
\end{aligned}$$

$$\lambda_i = \frac{\mu Var(\theta_j|s_j,s_i)+\lambda_j}{1-c_{p,j}}; \quad Var(\theta_i|s_i,s_j) = \sigma_\theta^2\frac{\sigma_i^2(1+\sigma_j^2-\rho^2)}{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2}$$

$$\xi_i^{otc} \equiv \big(\frac{1}{E[u_i]^2}-1\big) = \frac{\mu(\mu Var(\theta|s_i,p)+2\lambda_i)}{(\mu Var(\theta_i|s_i,p)+\lambda_i)^2}Var(E[\theta_i|s_i,p]-p).$$

Comparing the equilibrium utility in two markets,

$$\xi_i^{CM} > \xi_i^{OTC} \quad \Leftrightarrow \quad \frac{1+2\widehat{\lambda}_i^{cm}}{(1+\widehat{\lambda}_i^{cm})^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p_{cm})} > \frac{1+2\widehat{\lambda}_i^{otc}}{(1+\widehat{\lambda}_i^{otc})^2}\frac{Var(E[\theta_i|s_i,s_j]-p)}{Var(\theta|s_i,s_j)}.$$

If CM is worse than the minimum utility that a trader can get in OTC, in the sense that $E[u_i^{CM};\text{no one in CM}] < \min_{j;\rho_{ij}<0} E[u_i;OTC(i,j)]$, for all traders. Remark that it is a sufficient condition. When $\min_{j;\rho_{ij}<0} E[u_i;OTC(i,j)] < E[u_i^{CM}] < \max_j E[u_i;OTC(i,j)]$ for some traders, it can result in the extreme market structure, such as only centralized market or only over-the-counter market opens, depending on the over-the-counter matching outcome. ■

Proof of Corollary 1 (OTC Existence with a Competitive CM). From the proof of Theorem 1, the inequality (13) is a sufficient and necessary condition for a trader to prefer the centralized market to the over-the-counter market. Taking the number of traders in the centralized market I to infinity, the inequality is written as

$$(1-\bar{\rho}) > \frac{(2(1-\bar{\rho}))^2(\sigma^2+2\bar{\rho})^2 - (\sigma^2+2(1-\bar{\rho}))^2(2\bar{\rho})^2}{2(\sigma^2+2\bar{\rho})(\sigma^2+2\bar{\rho}\cdot 2(1-\bar{\rho}))},$$

and it is simplified into

$$0 > \sigma^2 - (3\sigma^2 + 2)\bar{\rho} + 2\bar{\rho}^2.$$

The inverse of this inequality is satisfied, so that the trader choose to enter to the over-the-counter market rather than to the centralized market, if and only if

$$1 - \bar{\rho} = \frac{\sigma_{iv}^2}{\sigma_{cv}^2 + \sigma_{iv}^2} > \frac{2 - 3\sigma^2 + \sqrt{(3\sigma^2 + 2)^2 - 8\sigma^2}}{4} > \frac{1}{2}, \tag{14}$$

which is equivalent to $\sigma^2 > \frac{2\bar{\rho}(1-\bar{\rho})}{3\bar{\rho}-2}$. The proof is complete. ■

Proof of Corollary 2 (No Price Difference in OTC and CM). Suppose that traders' asset values ($\tilde{\theta}_i = \theta + \delta_i$) follow the distributions $\theta \sim \mathcal{N}(E[\theta], \sigma_{cv}^2)$ and $\delta_i \sim \mathcal{N}(0, \sigma_{iv}^2 \Sigma)$ with $\Sigma = \left[\begin{array}{c|c} \mathbf{1} & -\mathbf{1} \\ \hline -\mathbf{1} & \mathbf{1} \end{array}\right]$ where $\mathbf{1} = (1)_{I/2 \times I/2}$ is a $(\frac{I}{2} \times \frac{I}{2})$-matrix with all elements being one, as in Example 1. In this model, the equilibrium price in the centralized market with a sufficiently large number of traders is $p_{cm} = \frac{1}{I}\sum_{i \in I} E[\theta + \delta_i | s_i, p] \approx \frac{c_\theta E[\theta] + c_s \theta}{c_\theta + c_s}$, since the average correlation of the idiosyncratic component (δ_i) is zero. On the other hand, the equilibrium price is determined in each over-the-counter matching between two traders whose correlation is $Corr(\delta_i, \delta_j) = -1$.

$$p_{otc} = \frac{c_\theta E[\theta_i] + c_s \frac{1}{2}(\theta + \delta_i + \varepsilon_i + \theta + \delta_j + \varepsilon_j)}{1 - c_p} = \frac{c_\theta E[\theta] + c_s \theta}{c_\theta + c_s} + \frac{c_s}{c_\theta + c_s}\big((\delta_i + \delta_j) + (\varepsilon_i + \varepsilon_j)\big) = p_{cm} + (\text{noise}).$$

Hence, the price p_{otc} in each over-the-counter market follows a normal distribution with the mean equal to the centralized market price p_{cm}. It shows that there exists a model where the over-the-counter and centralized market prices are same in expectation. Even in this case, a trader choose to trade in the over-the-counter market if the relative variance of idiosyncratic value component, $\frac{\sigma_{iv}^2}{\sigma_{cv}^2 + \sigma_{iv}^2}$, satisfies the inequality (14). ■

Proof of Theorem 2 (Coexistence of OTC and CM). Suppose that traders are symmetric in the sense that the profile of correlation in each row is same and that the information precision is same across traders (See Definition 2).

(i) With the symmetric correlation structure, a trader is matched with the counterparty whose asset valuations has the minimum correlation, i.e., the over-the-counter matching (i, j) occurs such that $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \min_{k \neq i} Corr(\tilde{\theta}_i, \tilde{\theta}_k) = \rho_{min}$, upon traders i and j's participation in the over-the-counter market. It can be shown as a contradiction on the symmetricity of traders. Suppose that there is an over-the-counter matching (i, j) such that $Corr(\tilde{\theta}_i, \tilde{\theta}_j) \gneq \rho_{min}$. Since the profile of correlations are same across traders, there exists another trader $k \neq i, j$ who has the minimum correlation with trader i, $Corr(\tilde{\theta}_i, \tilde{\theta}_k) = \rho_{min}$. If trader k's current matching in the over-the-counter market is not with the minimum correlation, traders i and k have a positive incentive to deviate from their current matchings, and thus the current matchings are not pair-wise stable.Therefore, trader k's current matching (k, l) has to be such that $Corr(\tilde{\theta}_k, \tilde{\theta}_l) = \rho_{min}$.

It implies that trader k has two other traders i and l that provides the minimum correlation ρ_{min}. By the symmetry, the profile of correlations of trader i, $\{Corr(\tilde{\theta}_i, \tilde{\theta}_m)\}_{i,m}$, contains two or more ρ_{min}, in that there exists another trader $m \neq i, j, k$ such that $Corr(\tilde{\theta}_i, \tilde{\theta}_m) = \rho_{min}$. With the same argument, the current matching for trader m has the minimum correlation, while implies that there are three or more ρ_{min} in the correlation profile. Recursively, the symmetricity of traders and pair-wise stable matching concludes that all pairs of traders have $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \rho_{min}$, which is a contradiction to the assumption that there exists (i, j)-match with $Corr(\tilde{\theta}_i, \tilde{\theta}_j) \gneq \rho_{min}$. Therefore, all over-the-counter matching in equilibrium satisfies $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \min_{k \neq i} Corr(\tilde{\theta}_i, \tilde{\theta}_k) = \rho_{min}$, $\forall (i, j)$.

(ii) By the part (i), the utility comparison between centralized and over-the-counter market is same for all traders. More formally, ρ^{otc}_{ij} and $\bar{\rho}^{cm}$ in two markets, and thus, the difference of these two correlations are fixed and symmetric for all traders. With the fixed correlation difference and the symmetric information precision, the incentive to enter either market is determined only by the different market size between the over-the-counter ($N = 2$) and centralized ($L + I$) markets. Suppose that a trader i who is currently in the over-the-counter market has a profitable deviation to the centralized market. After trader i's deviation, the market size in the centralized market increases. With the fixed correlation difference, the incentive to deviate from the over-the-counter to centralized market for other traders $j \neq i$ with $m_j = OTC$, i.e. for those who are currently in the over-the-counter market, is even stronger than the trader i. Applying this argument recursively, all traders choose the centralized market with endogenized market choice. The opposite direction of deviation also concludes that if there exists a trader who is currently in the centralized market and has a strictly positive incentive to deviate to the over-the-counter market, then all traders have the same incentive by the symmetricity. Therefore, it completes the proof for that the endogenous distribution of traders in the over-the-counter and centralized market has a corner solution if traders are symmetric. Equivalently, it concludes that two trading venues coexist only if traders are asymmetric. ■

Proof of Proposition 3 (OTC Matching with Heterogeneous Correlations). The pair-wise stable over-the-counter matching is determined by the following algorithm: (i) Upon traders' entry to the over-the-counter market, two traders, who have the most negative correlation among all pairs, are matched: we call this pair (i_1, j_1). (ii) If there are multiple pairs that have the most negative correlation, select one pair randomly. (iii) Eliminating the selected traders, select the most negative correlation among the remaining paper and create another pair: called (i_2, j_2). (iv) Repeating this procedure until there is at most one remaining trader in the over-the-counter market, and then the over-the-counter matching is determined $\{(i_t, j_t)\}_{t=1,2,\cdots}$.

It suffices to show that the matching $\{(i_t, j_t)\}_{t=1,2,\cdots}$ from this algorithm is pairwise stable. Suppose that there exists two traders who have a strictly positive incentive to deviate from their current matching and create their own matching. Formally, there exists i_t and j_s, for some $t \lneq s$, such that $E[u_{i_t}; OTC, (i_t, j_s)] \gneq E[u_{i_t}; OTC, (i_t, j_t)]$ and $E[u_{j_s}; OTC, (i_t, j_s)] \gneq$

$E[u_{j_s}; OTC, (i_s, j_s)]$. From Proposition 2, it implies that $Corr(i_t, j_s) \lneq Corr(i_t, j_t)$ and $Corr(i_t, j_s) \lneq Corr(i_s, j_s)$, since traders are symmetric in information precision and any bilateral trade has the equal market size $N = 2$. It is a contradiction to the algorithm: at the step (i) for t, the matching at t is created between (i_t, j_t), and hence, $Corr(i_t, j_t) \leq Corr(i_t, j_s)$ for any $s > t$. It is contradicted to the assumption that trader i_t has a profitable deviation by having another counterparty j_s, $Corr(i_t, j_s) \lneq Corr(i_t, j_t)$. The proof is complete. ■

Proof of Proposition 4 (Trade-Off in Learning and Price Impact over Precision). First, we characterize the equilibrium in a given over-the-counter bilateral matching between two traders i and j. Here, the correlation between two traders' asset values are ρ and information precision is $\phi_i = 1/\sigma_i^2$ and $\phi_j = 1/\sigma_j^2$.

$$c_{s,i} = \frac{\Gamma_i^2(1+\sigma_j^2+\rho) - \rho(1+\sigma_i^2+\rho)}{(1+\sigma_i^2)\Gamma_i^2(1+\sigma_j^2+\rho) - \rho(1+\sigma_i^2+\rho)}; \quad c_{p,i} = \frac{(\frac{1-c_{p,i}}{c_{s,i}} + \frac{1-c_{p,j}}{c_{s,j}}\Gamma_i)\rho\sigma_i^2}{(1+\sigma_i^2)\Gamma_i^2(1+\sigma_j^2+\rho) - \rho(1+\sigma_i^2+\rho)},$$

where $\Gamma_i = \frac{c_{s,j}}{\mu Var(\theta_j|s_j,p)+\lambda_j} / \frac{c_{s,i}}{\mu Var(\theta_i|s_i,p)+\lambda_i}$ and $\Gamma_j = 1/\Gamma_i$. Moreover,

$$Var(E[\theta_i|s_i,p]-p) = \sigma_\theta^2 c_{s,i}^2\big((1+\sigma_i^2) + \frac{(1+\sigma_i^2)+\Gamma_i^2(1+\sigma_j^2)+2\Gamma_i\rho}{(1+\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}}\Gamma_i)^2} - 2\frac{(1+\sigma_i^2)+\Gamma_i\rho}{(1+\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}}\Gamma_i)}\big),$$

$$\lambda_i = \frac{\mu Var(\theta_j|s_j,p)+\lambda_j}{1-c_{p,j}}; \quad \hat{\lambda}_i = \frac{Var(\theta_j|s_j,p)}{Var(\theta_i|s_i,p)}\frac{1+\hat{\lambda}_j}{1-c_{p,j}}; \quad Var(\theta_i|s_i,p) = \sigma_\theta^2\frac{\sigma_i^2(1+\sigma_j^2-\rho^2)}{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2}.$$

The equilibrium utility is derived as follows:

$$\xi_i(i,j) = \big(\frac{1}{E[u_i;(i,j)]^2} - 1\big) = \frac{1+2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)}.$$

By taking a derivative of equilibrium utility of trader i with respect to the information precision ϕ_j of trader j, the optimal counterparty $\phi_j^* = 1/(\sigma_j^2)^* \equiv arg\max_{\phi_j=1/\sigma_j^2}\xi_i(i,j)$ of trader i is determined by the first-order condition.

$$\big(\frac{\partial}{\partial\sigma_j^2}\frac{1+2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^2}\big)\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)} + \frac{1+2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^2}\big(\frac{\partial}{\partial\sigma_j^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)}\big) = 0.$$

Here, the partial derivatives of liquidity and learning effect with respect to the counterparty j's noise variance σ_j^2 satisfy the following equations.

$$\frac{\partial}{\partial \sigma_j^2}\frac{1+2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^2} = \frac{-2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^3}\frac{\partial}{\partial \sigma_j^2}\frac{V(\theta_j|s_j,p)(1-c_{p,i})+1}{(1-c_{p,i})(1-c_{p,j})-1}$$
$$= \frac{-2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^3}\frac{\frac{\partial V(\theta_j|s_j,p)}{\partial \sigma_j^2}(1-c_{p,i})((1-c_{p,i})(1-c_{p,j})-1)+\frac{\partial c_{p,i}}{\partial \sigma_j^2}(1-c_{p,j})+\frac{\partial c_{p,j}}{\partial \sigma_j^2}(1-c_{p,i})+V(\theta_j|s_j,p)\frac{\partial c_{p,j}}{\partial \sigma_j^2}((1-c_{p,i})^2+1)}{((1-c_{p,i})(1-c_{p,j})-1)^2},$$
$$\frac{\partial}{\partial \sigma_j^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)} = \frac{\frac{\partial Var(E[\theta_i|s_i,p]-p)}{\partial \sigma_j^2}Var(\theta_i|s_i,p)-\frac{\partial Var(\theta_i|s_i,p)}{\partial \sigma_j^2}Var(E[\theta_i|s_i,p]-p)}{(Var(\theta_i|s_i,p))^2}$$
$$= \frac{\partial}{\partial \sigma_j^2}\Big(\frac{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2}{\sigma_i^2(1+\sigma_j^2-\rho^2)}c_{s,i}^2\Gamma_i^2\frac{(1+\sigma_i^2)(\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}})^2-2\rho\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}}+(1+\sigma_j^2)}{(1+\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}}\Gamma_i)^2}\Big),$$

where $\frac{\partial c_{p,i}}{\partial \sigma_j^2} = \frac{(\frac{1-c_{p,i}}{c_{s,i}}+\frac{1-c_{p,j}}{c_{s,j}}\Gamma_i)\rho\sigma_i^2(1+\sigma_i^2)\Gamma_i^2}{((1+\sigma_i^2)\Gamma_i^2(1+\sigma_j^2+\rho)-\rho(1+\sigma_i^2+\rho))^2} > 0$, $\frac{\partial c_{p,j}}{\partial \sigma_j^2} = \frac{(\frac{1-c_{p,i}}{c_{s,i}}+\frac{1-c_{p,j}}{c_{s,j}}\Gamma_i)\rho(\Gamma_j^2(1+\sigma_i^2+\rho)-\rho(1+\rho))}{((1+\sigma_j^2)\Gamma_j^2(1+\sigma_i^2+\rho)-\rho(1+\sigma_j^2+\rho))^2} < 0$, $\frac{\partial Var(\theta_j|s_j,p)}{\partial \sigma_j^2} = \sigma_\theta^2\frac{(1+\sigma_i^2-\rho^2)^2}{((1+\sigma_j^2)(1+\sigma_i^2)-\rho^2)^2} > 0$, and $\frac{\partial Var(E[\theta_i|s_i,p]-p)}{\partial \sigma_j^2} = \frac{1}{(1+\frac{1-c_{p,j}}{1-c_{p,i}}\frac{c_{s,i}}{c_{s,j}}\Gamma_i)^2} > 0$. Hence, $\frac{\partial}{\partial \sigma_j^2}\frac{1+2\hat{\lambda}_i}{(1+\hat{\lambda}_i)^2} > 0$ so that the liquidity effect of trader i decreases as the precision of trader j increases (i.e., the noise variance σ_j^2 of trader j decreases). In addition, $\frac{\partial}{\partial \sigma_j^2}\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)} < 0$ if $\frac{Var(E[\theta_i|s_i,p]-p)}{Var(\theta_i|s_i,p)}$ is sufficiently large, in the sense that the precision of both traders i and j is sufficiently small. Under this condition, the learning effect i increases in the precision of the other trader j. This proves the trade-off between liquidity and learning effects with respect to the counterparty j's information precision ϕ_j. ■

Lemma 1 *There is no over-the-counter matching between two players who have positively correlated asset values. In that, if $Corr(\tilde{\theta}_i, \tilde{\theta}_j) = \rho_0 > 0$, then neither of trader i nor j choose the other as his counterparty.*

Proof. What we want to prove is that there is no equilibrium in the bilateral trade. From the assumption that no equilibrium leads to no trade, the incentive to choose the other as a counterparty is zero. The equilibrium price is

$$p^* = \left(\frac{1-c_{p1}}{\mu+\lambda_1}+\frac{1-c_{p2}}{\mu+\lambda_2}\right)^{-1}\left(\frac{c_{s1}s_1}{\mu+\lambda_1}+\frac{c_{s2}s_2}{\mu+\lambda_2}+(\frac{c_{\theta 1}}{\mu+\lambda_1}+\frac{c_{\theta 2}}{\mu+\lambda_2})\theta\right).$$

Therefore, the equilibrium price impact is characterized by

$$\lambda_i = \frac{\mu+\lambda_j}{1-c_{pj}} = \frac{\mu(2-c_{pi})}{(1-c_{pi})(1-c_{pj})-1} > 0, \qquad i \neq j \in \{1,2\}.$$

The characterization implies that the positivity condition for price impact $\lambda_i > 0, i = 1,2$ implies that $c_{pi} < 1$ for both $i = 1,2$. By the projection theorem, the endogenous coefficients $(c_{si}, c_{pi}, c_{\theta i}, \lambda_i)_{i=1,2}$ are the fixed-point solution of the following system of equations: with $c_{si} +$

$c_{pi} + c_{\theta i} = 1,$

$$c_{si} = \frac{((\frac{c_{sj}}{\mu+\lambda_j})(1-\rho^2+\frac{\sigma^2_{\varepsilon,j}}{\sigma^2_\theta}) - \frac{c_{si}}{\mu+\lambda_i}\rho\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_\theta})}{(\frac{c_{sj}}{\mu+\lambda_j})((1+\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_\theta})(1+\frac{\sigma^2_{\varepsilon,j}}{\sigma^2_\theta})-\rho^2)}, \quad c_{pi} = \frac{\left(\frac{1-c_{pi}}{\mu+\lambda_i}+\frac{1-c_{pj}}{\mu+\lambda_j}\right)\rho\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_\theta}}{(\frac{c_{sj}}{\mu+\lambda_j})((1+\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_\theta})(1+\frac{\sigma^2_{\varepsilon,j}}{\sigma^2_\theta})-\rho^2)}, \quad i \neq j \in \{1,2\}.$$

From the further calculation, we get the following explicit solution[15]

$$\begin{aligned}
c_{si} &= \frac{(1-\rho^2+\sigma_i^2)(1-\rho^2+\sigma_j^2)-\rho^2\sigma_i^2\sigma_j^2}{(1-\rho^2+\sigma_i^2+\frac{\mu+\lambda_j}{\mu+\lambda_i}\rho\sigma_i^2)((1+\sigma_i^2)(1+\sigma_j^2)-\rho^2)} = \frac{1-\rho^2}{1-\rho^2+\sigma_i^2+\frac{\mu+\lambda_j}{\mu+\lambda_i}\rho\sigma_i^2} \\
c_{pi} &= \frac{4\rho\sigma_i^2(1+\rho+\sigma_j^2)}{(1-\rho^2+\sigma_i^2)(1+\rho+\sigma_j^2)+(1-\rho^2+\sigma_j^2)(1+\rho+\sigma_i^2)+2\rho\sigma_i^2(1+\rho+\sigma_j^2)}
\end{aligned}$$

$$\begin{aligned}
\lambda_i &= -\mu\frac{(1-\rho^2+\sigma_i^2)(1+\rho+\sigma_j^2)+(1-\rho^2+\sigma_j^2)(1+\rho+\sigma_i^2)+2\rho\sigma_j^2(1+\rho+\sigma_i^2)}{2\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}} \\
&= -\mu\left\{\frac{1}{2\rho}-\frac{(1-\rho^2)(2+2\rho+\sigma_i^2+\sigma_j^2)}{2\rho\{(1+\rho)(\sigma_i^2+\sigma_j^2)+2\sigma_i^2\sigma_j^2\}}-\frac{\sigma_j^2(1+\rho+\sigma_i^2)}{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)}\right\}.
\end{aligned}$$

Here, the positivity condition for the price impacts, $\lambda_i > 0, \lambda_j > 0$, is equivalent to $\rho < 0$. Hence, when two traders' asset values have a non-negative correlation $Corr(\tilde{\theta}_i, \tilde{\theta}_j) < 0$, there is no equilibrium. ■

Proposition 6 (OTC matching equilibrium) *The over-the-counter market is in form of cross-type matching, if and only if*

$$\begin{aligned}
&\frac{\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}(1+\rho+\sigma_i^2)(1-\rho^2+\sigma_j^2)(L-2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{4(1+\rho)^2\{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2\}^2(L-2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2} \\
&\times\left\{\begin{array}{c}
\frac{(1+\sigma_i^2)(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}]^2}+\frac{(1+\sigma_j^2)(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{[(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]^2} \\
-\frac{2\rho(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}][(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]}
\end{array}\right\} \\
&\geq \frac{\sigma_i^2(1-\rho^2+\sigma_i^2)}{(1+\rho+\sigma_i^2)^2(1-\rho+\sigma_i^2)},
\end{aligned}$$

for all $i \neq j$, when $L = (1-\rho^2+\sigma_i^2)(1+\rho+\sigma_j^2)+(1-\rho^2+\sigma_j^2)(1+\rho+\sigma_i^2)$.

Proof. The same-group matching gives a trader with σ_i^2 his expected utility as follows:

$$E[u_i^{same}] = \frac{\mu+2\lambda}{(\mu+\lambda)^2}\frac{c_s^2}{4}(1+\sigma_i^2-\rho) = -\frac{\rho\sigma_i^2(1-\rho^2+\sigma_i^2)}{\mu(1+\rho+\sigma_i^2)^2(1-\rho+\sigma_i^2)}$$

[15]As special cases, the above fixed-point problem provides that (a) in a symmetric case, $c_s = \frac{1-\rho}{1-\rho+\sigma^2}, c_p = \frac{2\rho\sigma^2}{(1+\rho)(1-\rho+\sigma^2)}$, and that (b) if $\sigma^2_{\varepsilon,j} = \infty$, $c_{si} = \frac{1}{1+\sigma_i^2}, c_{pi} = 0$ and $c_{sj} = 0, c_{pj} = \frac{2\rho}{1+\rho/2}$.

where $\lambda = -\mu\frac{(1+\rho)(1-\rho+\sigma_i^2)}{2\rho\sigma_i^2}$, $c_s = \frac{1-\rho}{1-\rho+\sigma_i^2}$. In addition, the cross-group matching gives equilibrium utility as follows:

$$E[u_i^{cross}] = \frac{\mu+2\lambda_i}{2(\mu+\lambda_i)^2}\left(\frac{1}{\lambda_i}+\frac{1}{\lambda_j}\right)^{-2}\left((\frac{c_{si}}{\lambda_i})^2(1+\sigma_i^2)+(\frac{\mu+\lambda_i}{\mu+\lambda_j}\frac{c_{sj}}{\lambda_j})^2(1+\sigma_j^2)-2\frac{c_{si}}{\lambda_i}\frac{\mu+\lambda_i}{\mu+\lambda_j}\frac{c_{sj}}{\lambda_j}\rho\right).$$

Hence, the condition for that the cross-group matching is the equilibrium in OTC,

$$E[u_i^{cross}] \geq E[u_i^{same}], \quad \forall\ i \in \{in, un\},$$

can be characterized with the equilibrium parameters of cross-type matching. When $L = (1-\rho^2+\sigma_i^2)(1+\rho+\sigma_j^2)+(1-\rho^2+\sigma_j^2)(1+\rho+\sigma_i^2)$, the parameters $\{\lambda_i, \lambda_j\}$ have a closed form solution.

$$\mu+2\lambda_i = \mu\frac{\rho(1+\rho)(\sigma_i^2-\sigma_j^2)-L}{\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}}.$$

This provides the closed-form solution of equilibrium utility in the cross-type matching, from the following derivations.

$$\begin{aligned}
\frac{\mu+2\lambda_i}{2(\mu+\lambda_i)^2} &= \frac{2\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}\left(\rho(1+\rho)(\sigma_i^2-\sigma_j^2)-L\right)}{\mu(2\rho\sigma_i^2(1+\rho+\sigma_j^2)-L)^2} \\
\frac{1}{\lambda_i}+\frac{1}{\lambda_j} &= -\frac{4\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}\left(L+\rho\left\{\sigma_j^2(1+\rho+\sigma_i^2)+\sigma_i^2(1+\rho+\sigma_j^2)\right\}\right)}{\mu(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))} \\
\frac{\mu+2\lambda_i}{2(\mu+\lambda_i)^2}\left(\frac{1}{\lambda_i}+\frac{1}{\lambda_j}\right)^{-2} &= \frac{(\rho(1+\rho)(\sigma_i^2-\sigma_j^2)-L)}{(L-2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2}\frac{\mu(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2}{8\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}\left(L+\rho\left\{\sigma_j^2(1+\rho+\sigma_i^2)+\sigma_i^2(1+\rho\right.\right.} \\
\frac{\mu+\lambda_i}{\mu+\lambda_j}\frac{c_{sj}}{\lambda_j} &= \frac{-2\rho(1-\rho^2)\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}(L-2\rho\sigma_j^2(1+\rho+\sigma_i^2))}{\mu(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))[(1-\rho^2+\sigma_j^2)(L-2\rho\sigma_i^2(1+\rho+\sigma_j^2))+\rho\sigma_j^2(L-2\rho\sigma_j^2(1+\rho+\sigma_i^2))]}.
\end{aligned}$$

Hence, we get

$$\begin{aligned}
E[u_i^{cross}] &= \frac{-\rho\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}(1+\rho+\sigma_i^2)(1-\rho^2+\sigma_j^2)(L-2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{4\mu(1+\rho)^2\{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2\}^2(L-2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2} \\
&\quad \times\left\{\begin{array}{c}
\frac{(1+\sigma_i^2)(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}]^2}+\frac{(1+\sigma_j^2)(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{[(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]^2} \\
-\frac{2\rho(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}][(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]}
\end{array}\right\}.
\end{aligned}$$

The sufficient and necessary condition on $E[u_i^{some}] \leq E[u_i^{cross}]$, subject to existence, is as follows:

$$\begin{aligned}
& \frac{\left\{\sigma_i^2(1+\rho+\sigma_j^2)+\sigma_j^2(1+\rho+\sigma_i^2)\right\}(1+\rho+\sigma_i^2)(1-\rho^2+\sigma_j^2)(L-2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{4(1+\rho)^2\{(1+\sigma_i^2)(1+\sigma_j^2)-\rho^2\}^2(L-2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2} \\
& \times \left\{ \begin{array}{c} \frac{(1+\sigma_i^2)(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))^2}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}]^2} + \frac{(1+\sigma_j^2)(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))^2}{[(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]^2} \\ -\frac{2\rho(L+2\rho\sigma_j^2(1+\rho+\sigma_i^2))(L+2\rho\sigma_i^2(1+\rho+\sigma_j^2))}{[(1+\rho+\sigma_i^2)\{2(1+\rho+\sigma_j^2)(1-\rho+\sigma_i^2)+\rho(\sigma_i^2-\sigma_j^2)\}][(1+\rho+\sigma_j^2)\{2(1+\rho+\sigma_i^2)(1-\rho+\sigma_j^2)+\rho(\sigma_j^2-\sigma_i^2)\}]} \end{array} \right\} \\
\geq \; & \frac{\sigma_i^2(1-\rho^2+\sigma_i^2)}{(1+\rho+\sigma_i^2)^2(1-\rho+\sigma_i^2)}
\end{aligned}$$

Comparing the expected utilities $E[u_i^{some}]$ and $E[u_i^{cross}]$ from same-type and cross-type matching, the sufficient and necessary condition for over-the-counter matching to be between informed and uninformed traders in equilibrium. ■

Bank Competition and Bank Liquidity Creation*

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Abstract: Using comprehensive measures of bank liquidity creation by Berger and Bouwman (2009), I investigate empirically whether bank competition affects bank liquidity creation among 16367 banks from 1984 to 2007. I find that bank-level competition affects bank's liquidity creation strategy. Using bank-level competition measure, I find that banks create less liquidity when the market is more competitive. Exploiting intra- and interstate bank deregulations and interstate bank branching deregulation, I find that banks create less liquidity as interstate branching restrictions release but banks do not significantly respond to intra- and interstate banking deregulation. Surprisingly, different from bank-level analysis, state-level analysis shows that bank deregulation events do not significantly affect state-level bank liquidity creation on average. The results highlight the role of proper regulation to encourage depressed credit market in the United States.

***Keywords**:* Bank Competition, Bank Liquidity Creation, Deregulation, Government Regulation

JEL Classification: G21, G28, G32

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1. Introduction

The two central roles that banks play in the economy are risk transformation and liquidity creation. Since banks have the advantage of economies of scale, they can transform risk by issuing riskless deposits to finance risky loans. This risk transformation may coincide with liquidity creation. As these two main roles are crucially important in the economy, there are many previous studies of them. However, the past literature mostly leans toward the banks' role as risk transformers, even though their role as liquidity creators is an essential part of banking, and interest in bank liquidity creation increases after the recent financial crisis (e.g., Ivashina and Scharfstein, 2010).

The reason why empirical studies examining theoretical views of bank liquidity creation are rare is the absence of a comprehensive measure of bank liquidity creation. However, Berger and Bouwman (2009) provide comprehensive bank liquidity creation measures that allow us to investigate empirical research questions about a bank's role as a liquidity creator. They classify balance sheet activities as liquid, semi-liquid, or illiquid. Once all of the balance sheet activities are classified, the authors assign weights, which are ranged from -0.5 to 0.5, and calculated the measures by summing all weighted activities. The specifications classify all items except loans by combining information on both product category and maturity, while loans are classified based purely on either category or maturity (i.e., "cat" or "mat" measures) because of the lack of data availability. In addition, off-balance-sheet items are either included or excluded (i.e., "fat" or "nonfat" measures).

Bank competition is a popular issue in banking research: both theoretical and empirical literature on the topic has emerged. The previous literature about bank competition mostly focuses on its impact on financial stability, risk-taking, access to credit, and bank failure. Two views of competition—"competition-fragility" and "competition-stability"—are posited in the literature. Even though some studies find empirical evidence for each view, the findings of the empirical research that explores the links between competition and risk are rather mixed and still inconclusive. For example, Berger, Klapper, and Turk-Ariss (2009) find limited support for both the competition-fragility and the competition-stability views. However, there has not been enough discussion about the effect of bank competition on bank liquidity creation. Thus, in this paper, I examine whether bank competition affects bank liquidity creation, using a panel dataset of U.S. banks from 1984 to 2007.

Like bank competition literature, the empirical results of my research could also have mixed evidence. On the one hand, I expect a positive relationship between bank competition and bank liquidity creation. For example, less bank competition (i.e., more market power) may induce banks to raise lending interest rates and, thus, firms to have lower demands for borrowing money from banks, because the banks with a higher level of market power dominate the market. Also, the banks may raise loan rates and lower deposit rates when the market becomes less competitive, which means that banks would have more market power to increase their charter value. From this point of view, large banks are likely to create less liquidity in the market when their market power is significant. Compared to smaller banks, large banks have a more secured buffer for overcoming unexpected financial shocks, because they have several different branches, and each branch would have different market conditions. These variations among different branches of the large banks could be considered as a way of hedging against risk. That is why the large banks could pursue a strategy creating less liquidity, which is an aggressive strategy for maximizing their profit when they dominate the market. Thus, banks in a less competitive market might create less liquidity, and banks in a more competitive market would create more liquidity.

On the other hand, I expect a negative relationship between bank competition and bank liquidity creation. Less bank competition might induce banks to provide more liquidity. For instance, banks supply more loans when the market becomes more concentrated, because the banks are likely to take on more risk when they have more market power. Also, banks in a less competitive market may provide more liquidity because they can supply more loans through relationship banking while taking more deposits. Banks focusing on relationship banking could create more liquidity to keep the relationship with their borrowers. From this point of view, banks would create more liquidity in the market when they have more market power (i.e., when they are less competitive).

To test these hypotheses, I construct a panel dataset for the sample period between 1984 and 2007. The data covers almost all the commercial banks in the United States. I collect the data from various sources such as Call Reports, DealScan, Summary of Deposits surveys, the Federal Housing Finance Agency, the U.S. Census Bureau, the U.S. Department of the Treasury, and Christa Bouwman's personal website.

Following previous studies regarding bank competition (e.g., Fernandez de Guevara, Maudos, and Perex, 2005; Berger, Klapper, and Turk-Ariss, 2009; Koetter, Kolari, and Spierdijk, 2012; Jimenez, Lopez, and Saurina, 2013; and Berger and Roman, 2015), I use the Lerner Index for gross total assets (GTA), which is calculated as the observed price-cost margin divided by price, as a proxy for bank competition, which is a key independent variable in this research. The value of the Lerner Index ranges from 0 to 1. A 0 value on the Lerner Index means perfect competition, and when the value of Lerner Index is equal to 1, a monopoly is considered to exist. Thus, banks with any degree of market power except the two extremes have a positive Lerner Index value. In addition, I exploit the U.S. banking deregulation events, including intra- and interstate deregulation and interstate branching deregulation, as exogenous shocks on bank competition (e.g., Johnson and Strahan, 2008; Rice and Strahan, 2009; Koetter, Kolari, and Spierdijk, 2012; Chava, Oettl, Subramanian, and Subramanian, 2013; Krishnan, Nandy, and Puri, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015).

Based on Berger and Bouwman (2009), I choose the most comprehensive bank liquidity creation measure, "catfat," among four different bank liquidity creation proxies to measure bank liquidity creation. This is a key dependent variable among the various specifications in this paper. In addition, there could be endogeneity issues such as reverse causality and omitted variables. For example, banks that create more liquidity may have higher market power. Also, it is possible that many other factors affecting both bank liquidity creation and bank competition are unobservable. Thus, I used multiple empirical approaches, including a fixed-effects model and difference-in-differences estimation, to mitigate these endogeneity problems.

Using the panel dataset that includes all sample banks, I find that reverse relationship between bank competition and bank liquidity creation. In other words, banks with a higher level of market power create more liquidity in the market. At this stage, I could not check whether this result is caused by reaping monopolistic rents or maintaining a relationship with borrowers. To disentangle these effects, I split the sample into large, medium-sized, and small banks and test whether the negative relationship exists for every size class of banks or only for specific size classes. Through the subsample analysis by bank size, I find that only small-sized banks significantly create more liquidity in the market as bank competition decreases. However, I do not claim causal relation because of endogeneity concerns.

Following previous studies exploiting U.S. intra- and interstate banking deregulation and interstate branching deregulation as exogenous shocks on bank competition (e.g., Johnson and Strahan, 2008; Rice and Strahan, 2009; Koetter, Kolari, and Spierdijk, 2012; Chava, Oettl, Subramanian, and Subramanian, 2013; Krishnan, Nandy, and Puri, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015), I exploit the exogenous variation in bank competition using the U.S. banking deregulation events. Intrastate deregulation allows banks to merge or acquire other banks inside the market where they are located. In contrast, interstate deregulation allows banks to acquire a commercial bank in deregulated states. More importantly, interstate branching deregulation allows out-of-state banks to acquire a branch in the deregulated states and the level of openness varies over time.

The results of analysis using the deregulation events are consistent with the results of analysis using the Lerner Index as a bank competition measure. Exploiting intra- and interstate bank deregulations, I find that banks do not significantly respond to both intra- and interstate banking deregulation. However, exploiting interstate bank branching deregulation, I find that interstate bank branching deregulation leads to reduction in bank liquidity creation. To be specific, banks create more liquidity as the level of interstate branching regulation in their home state increases. I also find that small banks create more liquidity than medium/large banks as branching restrictions release.

The results make sense because interstate deregulation requires much higher fixed costs to invest in deregulated states. Only sizable banks are able to acquire and/or establish a charter in a state outside the main bank's home state. On the other hand, small banks would not compete with the sizable competitors. That is why these two effects could offset each other. In addition, existing large banks in the deregulated state could have chance to invest in the other deregulated states. This could also affect the insignificant effects of interstate deregulation.

Interstate branching deregulation lowers fixed costs to invest in the deregulated states. Different from interstate bank deregulation, interstate branching deregulation allows banks to acquire a branch. For example, banks in highly restrictive states would be secured than banks in highly open states in terms of the outside threat. In addition, they have much lower fixed costs to enter the new market after interstate branching deregulation. Thus, they have incentives to acquire or establish a new branch in the neighboring states, where the level of restrictiveness is lower than their home state. In this situation, large banks would create less liquidity to enjoy monopolistic rents and small banks would create less liquidity to avoid default risks. In a relative sense, smaller banks would create more liquidity than large banks to keep their relationship banking. This means that the negative effect of bank competition on bank liquidity creation is weaker for smaller banks.

Investigating bank-level relation between bank competition and bank liquidity creation is interesting and important. However, my results suggest that economic magnitude of bank-level analysis is not significant. Causal effects of interstate bank branching deregulation on bank-level liquidity creation suggest that completely open states generate a total of 1.82% less liquidity creation post branching deregulation than the most restrictive states.

In addition, for the perspective of regulators, bank-level analysis would not be important than aggregate state-level analysis because policy makers do care about local market economy. To derive policy implication concerning bank competition and bank liquidity creation, I examine state-level analysis.

Following Berger and Sedunov (2017), I test whether state-level bank competition affects state-level bank liquidity creation. To construct state-level liquidity creation and control variables, I rely on each bank's state deposit market shares as a proxy for weights on states where they operate branches. Interestingly, state-level analysis shows that bank deregulation events do not affect state-level bank liquidity creation on average. This result suggests that intra- and interstate bank deregulation and interstate branching deregulation do not really stimulate the depressed capital market. Based on both bank-level and state-level results, the key policy implication is that a policy to encourage bank competition would be more efficient if the policy applies to banks depending on banks' heterogeneity, such as bank size and bank market share, and markets' heterogeneity, such as market demand and supply-side competition status prior to the policy implementation.

My paper contributes the literature that investigates the effects of banking deregulation. Even though Jayaratne and Strahan (1996) find that interstate deregulation results in economic growth in local markets, results of my paper suggest that the effects might not be driven by banking activities because bank liquidity creation would be crucial bank-side activity to encourage local market growth.

Second, my paper contributes to the literature on bank liquidity creation. Because of lack of comprehensive bank liquidity creation measures, there is few empirical studies examining the determinants of bank liquidity creation and/or the effects of bank liquidity creation before Berger and Bouwman (2009) provide the comprehensive measure, which is catfat. This literature shows relations between liquidity creation and equity ratio (Berger and Bouwman, 2009), corporate governance (Diaz and Huang, 2017), and real economic output (Berger and Sedunov, 2017).

I am aware of a contemporaneous study by Jiang, Levine, and Lin (2016), which also examine the relationship between bank competition and bank liquidity creation. Based on interstate bank deregulation, they construct distance-weighted bank competition measures, which are continuous bank-level measures. Their measure considers the distance between each bank in the deregulated state and capital city of the other states as a factor of bank competition. Using the bank-level distance-weighted interstate deregulation measures, they find that regulatory-induced competition has a negative effect on bank liquidity creation.

Different from this study, I focus on both state-level and bank-level analyses that examine the effects of bank competition on bank liquidity creation. State-level analysis allows me to generate policy implications on bank competition. In addition, I exploit interstate bank branching deregulation, which would be more important on bank liquidity creation because decisions about loan and deposit contracts are made by branch managers. Same as Chava, Oettl, Subramanian, and Subramanian (2013) and Cornaggia, Mao, Tian, and Wolfe (2015), my paper and Jiang, Levine, and Lin (2016) suggest two different perspectives of bank deregulation.

The remainder of this paper is organized as follows. I first review the existing literatures on bank competition and bank liquidity creation. In Section 3, I develop testable hypotheses. Section 4 describes data and methodologies. Section 5 provides empirical results and Section 6 concludes.

2. Literature Review

2.1 Bank Competition

The deregulation of banking activities has drawn much attention of researchers and regulators on the role of competition in the banking industry. Previous literature about bank competition mostly focused on the impact of bank competition on financial stability, risk-taking, access to credit, and bank failure. However, there is not enough discussion about the effect of bank competition on bank liquidity creation.

There are two strands of literature on bank competition: "competition-fragility" and "competition-stability." The "competition-fragility" view suggests that enhanced bank competition results in reduced profit margins and franchise value, and this induce banks to take excessive risk. According to past literature on the view, profit margins play as a safeguard in the event of financial distress so banks try to recover their profit margins by taking excessive risk even though the projects are high risk projects (e.g., Repullo, 2004). In addition, banks tend to protect their franchise value when the market is more concentrated by taking less risk because high franchise value implies high opportunity costs of bank failure (e.g., Keeley, 1990; Hellmann, Murdock, and Stiglitz, 2000). Thus, the "competition-fragility" view supports the argument that higher level of bank competition would result in more fragility.

The second view of bank competition is the "competition-stability" view. This view argues that bank competition makes financial system more stable. That is, more concentrated market power could lead to higher bank risk and/or higher probability of bank failure. Past literature supporting the "competition-stability" argues that the more bank market power, the more bank risk exposure. This is because the dominant banks enjoy monopolistic rents, such as higher interest rates and lower deposit rates, through their market power and it could lead to adverse selection and risk shifting (e.g., Stiglitz and Weiss, 1981). Boyd and De Nicolo (2005) and Schaeck, Cihak, and Wolfe (2009) also support the "competition-stability" view. These studies suggest that the more market power, the less stable financial system. Different from previous studies, Boyd and De Nicolo (2005) construct models that allow bank competition for both deposit and loan markets, and they suggest the reverse relation between bank competition and bank failure. Less bank competition means more concentrated market power, and less bank competition could lead to higher loan rates and lower deposit rates because banks with higher level of market power have incentives to pursue monopolistic rents. Reduced bank competition could lead to either a more stable credit market, which is an intended result of government policy, or a highly dominated and limited credit market, which is an unexpected incident. Using 45 countries international data, Scaheck, Cihak, and Wolfe (2009) also support this view. They find that enhanced bank competition tends to be more stable and tend not to suffer systemic crisis.

However, Berger, Klapper, and Turk-Ariss (2009) take a moderate position because they find mixed empirical results about the effects of bank competition on financial stability. Berger, Klapper, and Turk-Ariss (2009) find that market power increases credit risk, but banks with more market power face less risk overall, using a variety of risk and competition measures derived from a dataset of banks located in 23 countries. Thus, the paper suggests limited support to both the competition-fragility and the competition-stability views. These mixed results suggest that the effects of bank competition on bank activities could also be mixed under heterogeneous circumstances.

2.2 Bank Liquidity Creation

There are many past studies that suggests the reason why banks exist is to create liquidity to borrowers and lenders (e.g., Bryant, 1980; Diamond and Dybvig, 1983; Gorton and Pennacchi, 1990; Holmstrom and Tirole, 1996; Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006). Banks create liquidity because they grant long-term and illiquid loans to borrowers by using short-term and liquid deposits. Bryant (1980) and Diamond and Dybvig (1983) argue that banks create liquidity on the balance sheet by financing relatively illiquid assets with relatively liquid liabilities. Also, Holmstrom and Tirole (1998) and Kashyap, Rajan, and Stein (2002) suggest that banks also create liquidity in form of loan commitments or credit lines. This means that banks create liquidity off the balance sheet as well. Loan commitments can give a borrower the option to draw down them on demand during the period of the contract. These withdrawals are uncertain to the bank. From the perspectives of customers, loan commitments provide liquidity whenever they require liquidity unexpectedly.

Empirical studies concerning about bank liquidity creation are relatively insufficient because of the absence of comprehensive measure of bank liquidity creation. Deep and Schaefer (2004) develop Liquidity Transformation gap as a measure of liquidity creation, but it is not comprehensive measure. Berger and Bouwman (2009) provide four measures of liquidity creation and argue that catfat measure is better than other measures including Liquidity Transformation gap, which is similar to matnonfat measure of Berger and Bouwman (2009). Different from Liquidity Transformation gap, catfat liquidity creation measure classifies loans by category, rather than by maturity. This measure treats business loans as illiquid regardless of their maturity because banks generally cannot easily dispose of them to meet liquidity needs, but this measure treats residential mortgages and consumer loans as semiliquid because these loans can often be securitized and sold to meet demands for liquid funds. Also, catfat includes off-balance sheet activities as well as on-balance sheet activities. Thus, catfat measure is advanced and more comprehensive measure of liquidity creation.

Berger and Bouwman (2009) construct a comprehensive measure of bank liquidity creation by including off-balance sheet items and by considering categories rather than maturities. There is three-step procedure to construct the liquidity creation measures. In Step 1, all balance sheet and off-balance sheets activities are classified as liquid, semi-liquid, or illiquid. The classification is based on the ease, cost, and time for customers to obtain liquid funds from the bank, and the ease cost, and time for banks to dispose of their obligations to meet these liquidity demands. The balance sheet items are classified by product category and maturity. In Step 2, weights are assigned to the items classified in Step 1. In Step 3, liquidity creation is measured by combining the items as classified in Step 1 and as weighted in Step 2.

Using virtually all U.S. commercial banks from 1993 to 2003, they find that the U.S. banking industry creates $2.84 trillion in liquidity in 2003, which is equivalent to $4.56 of liquidity creation per $1 of bank equity capital, and liquidity creation has grown substantially over the sample period by using catfat measure. They also report that the liquidity creation differs considerably among banks by different size. Banks categorized as large banks, about 2 percent of their sample, account for 81 percent of the bank liquidity creation. In addition, off-balance sheet items played a significant role in generating liquidity for banks of all sizes.

There are not enough studies examining the relationship between bank competition and bank liquidity creation. Three exceptions are Joh and Kim (2008), Horvath, Seidler, and Weill (2013), and Jiang, Lin, and Levine (2016). Different from my paper, first two papers use non-U.S. data to investigate the effects of bank competition on bank liquidity creation. Horvath, Seidler, and Weill (2013) investigate this research question but their dataset is from the Czech banking industry. They analyze the impact of bank competition on liquidity creation, using a dataset of Czech banks from 2002 to 2010. They find that enhanced competition reduces liquidity creation and suggest that pro-competitive policies in the banking industry can reduce liquidity provision by banks. However, they do not use catfat measure because of a lack of information about components of catfat measure. According to Berger and Bouwman (2009), catfat measure is the most comprehensive measure among the four liquidity creation measures because it includes off-balance sheet liquidity creation and classification for loans is based on category. Joh and Kim (2008) use an international data covering 25 OECD countries. They use catfat measure following Berger and Bouwman (2009) but they control for size and market shares even though the key explanatory variable is Lerner Index, which is strongly related to those variables. This could lead to biased results.

Different from these papers, my paper investigates the relationship between bank competition and bank liquidity creation, using the U.S. banking industry dataset. Also, I exploit exogenous variation in bank competition through the U. S. banking deregulation events, including intra- and interstate bank deregulation and interstate branching deregulation, and stick to use catfat measure using sufficient datasets.

3. Hypothesis Development

This section details my hypotheses. By examining these hypotheses, I figure out how bank competition affects banks' liquidity creation strategies in a variety of circumstances.

The first testable hypothesis is that the relationship between bank competition and bank liquidity creation is negative. In other words, I expect the positive effect of bank market power on bank liquidity creation. The basic idea behind this hypothesis is that, in the more competitive market, banks would suffer severe default risk and bank run risk. This is because many banks in the competitive market try to survive by reducing their risk exposure if their resources are concentrated on the market and they have no alternative market to move. By doing this, banks could keep a certain amount of cash holdings, which acts as a buffer against bank default risk and bank run risk. Thus, banks in the competitive market would create less liquidity in the market to avoid bank failure. From a perspective of bank market power, banks with higher level of market power would have enough sources of financing borrowers and have relatively sound internal stability to respond to unexpected financial shocks. This argument is in line with Petersen and Rajan (1995), suggesting that banks are less likely to supply credit when markets are more competitive (i.e. less concentrated). They argue it is difficult for banks to internalize the benefits of assisting the firms, so banks are less likely to grant credit to firms that do not have long-term relationship with the banks. In other words, banks have much worse accessibility to information on borrowers in the competitive market than in the concentrated market. Thus, banks have no incentive to create liquidity for new customers without reliable information about them. Banks could utilize their own cumulative information about existing long-term customers to evaluate underlying risks to create more liquidity in the market. From these two perspectives, I expect that the relationship between bank competition and liquidity creation is negative.

Hypothesis 1: Bank competition is negatively associated with bank liquidity creation.

As I discuss in the previous section, two different views on bank competition, which are "competition-fragility" and "competition-stability" views, could raise a possibility to have mixed empirical results about the effects of bank competition on bank liquidity creation. The first hypothesis is based on "competition-fragility" view. From the perspective of "competition-stability" view, it would be possible that the impact of bank competition on bank liquidity creation is positive.

Bank competition condition could affect banks' decision on loan pricing and deposit rate. To be specific, banks in more competitive market may reduce loan rates and increase deposit rate to increase demand for both loans and deposits (e.g., Carbo-Valverde, Rodriguez-Fernandez and Udell, 2009; Love and Martinez Peria, 2012). Also, on the other hand, less bank competition may induce banks to raise lending interest rates and thus firms have lower demands to borrow money from banks. In addition, Beck, Demirgüc-Kunt and Maksimovic (2004) suggest that keen competition increases demand for loans by alleviating financing obstacles, such as collateral, to dominate the market. This leads to higher liquidity creation. This could be a case for large banks. Because large banks have sufficient resources to compete with the other banks in the competitive market, they would tend to dominate the market when bank competition is severe. From the perspective of market power, the large banks with substantial market power would tend not to create liquidity with favorable terms because they have less default risk and bank run risk by possessing sufficient funds in several different markets. This mechanism would allow them to pursue monopolistic gains, such as higher loan rate and lower deposit rate. Thus, the effects of bank competition on bank liquidity creation would not inverse but direct.

Hypothesis 2: For large banks, bank competition is positively associated with bank liquidity creation.

Using proprietary data, Peterson and Rajan (1994) investigate the effects of relationship banking between banks and small firms on the availability and cost of financing. They find that relationship banking positively affects financing availability of the borrowers. They also find that a wide and shallow relationship with multiple lenders would result in both increase in costs and decrease in the availability of financing. These results suggest that bank competition condition affect the efficiency of relationship banking. In highly competitive market, there are many banks in the market to compete. In this case, borrowers have many different alternatives to finance. This would aggravate existing lender's private information about borrowers because new lenders can verify the private information. On the other hand, in less competitive market (i.e. more concentrated market), the existing lender could enjoy its informational monopoly because possibility that the private information is verified is quite low in this case. This would lead to availability of funds for the firms involving the relationship.

Peterson and Rajan (1995) also examine the effects of competition on relationship banking. Results of this paper suggest that creditors are more likely to finance credit-constrained firms when bank competition is less competitive because banks could internalize the benefits from the relationship banking more easily in the concentrated market. This suggests that banks would want to keep this information advantage in the concentrated market. Different from large banks, small banks with the long-term lending relationships would create more liquidity in the less competitive market. Because they do not have strong capabilities to build multiple deep relationships with borrowers, they would tend to utilize their own private information and try to maximize their profits under the constrained circumstance. From the view of bank competition, these small banks would not create liquidity aggressively to stand a chance in competition with the other banks because they have significant default risk and bank run risk in the highly competitive market. Thus, in this case, they would keep their liquidity to protect themselves against the risks.

Enhanced bank competition could either increase or decrease bank-level liquidity creation. In the competitive market, large banks would increase bank liquidity creation to dominate the market. On the other hand, large banks would not increase liquidity creation to enjoy monopolistic gains. Small banks would increase bank liquidity creation to keep their relationship banking, but it could be also possible that small banks would decrease liquidity creation to avoid the default risk in the competitive market.

Based on arguments that the market is segmented and that banks could react to bank competition differently, I expect that the effects of bank competition on bank-level liquidity creation could offset each other at state-level.

Hypothesis 3: For small banks, bank competition is negatively associated with bank liquidity creation.

Hypothesis 4: The effects of bank competition on bank-level bank liquidity creation would be offset at the state-level.

Previous studies exploit the U.S. banking deregulation as exogenous shocks on bank competition (e.g., Johnson and Strahan, 2008; Rice and Strahan, 2009; Koetter, Kolari, and Spierdijk, 2012; Chava, Oettl, Subramanian, and Subramanian, 2013; Krishnan, Nandy, and Puri, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015). These studies use the exogenous variation in bank competition after the banking deregulation. Theoretically, banking deregulation could increase bank competition, bank efficiency, and M&A activities. Also, this could improve local market macroeconomic condition (e.g., Jayaratne and Strahan, 1996). These studies suggest that intrastate banking deregulation and intrastate banking deregulation have different effects on banks. Intrastate deregulation enhances market concentration because number of competitions is fixed within the state. On the other hand, interstate deregulation leads to more competitive market because out-of-state banks can enter the deregulated states.

Based on arguments above, I expect that the effects of intrastate deregulation could be mixed. Generally, banks in the concentrated market through intrastate deregulation would create less liquidity because dominant players would want to exploit monopolistic rents. However, if the dominant players focus on relationship banking, then they could create more liquidity in the market to keep their relationship with borrowers.

The effects of interstate deregulation could be also mixed. This is because of relatively high fixed costs for acquiring and/or establishing a charter in deregulated states. Interstate bank deregulation does not allow out-of-state banks to acquire or establish a branch in the deregulated state. The deregulation only allows them to acquire or establish a chartered bank in the deregulated state. This means that the newcomers are more likely to be aggressive in terms of liquidity creation. Existing dominant banks in the state would also create more liquidity to compete with the incoming competitors if they have sufficient resources and there is no other investment option. If they have other investment opportunities, such as investment in the other deregulated states, they could create less liquidity in the home state and create more liquidity in the new market. In addition, smaller banks would create less liquidity creation to avoid default risks in the competitive market. Thus, I expect that the effects of interstate bank deregulation on bank liquidity creation would offset.

Interstate bank branching deregulation would have different effects on bank liquidity creation. Different from intra- and interstate bank deregulation, interstate branching deregulation lowers fixed costs to enter the deregulated markets. Banks in more restrictive states would be more secured than bank in more open states. Because the level of restrictiveness varies over time and the fixed cost acquiring a branch is much lower than the fixed cost acquiring a commercial bank, banks in relatively restrictive states could invest in a branch of the contiguous states, where the level of restrictiveness in terms of bank branching is lower than the bank's home state. Thus, I expect that interstate deregulation and interstate bank branching deregulation would have contrasting effects on bank liquidity creation and that the more restrictive interstate bank branching regulation would lead to more bank liquidity creation.

Hypothesis 5: The effects of intra- and interstate bank deregulation on bank liquidity creation would be mixed.
Hypothesis 6: The effects of interstate bank branching deregulation on bank liquidity creation would be negative.

4. Data and Methodology

4.1 Data

To investigate the effect of bank competition on bank liquidity creation, I construct an unbalanced panel of bank-level dataset for almost all commercial banks in the United States during the sample period between 1984 and 2007. I collect the data from various sources such as Call Reports, Summary of Deposits, DealScan, Federal Housing Finance Agency, United States Census Bureau, the U.S. Department of the Treasury, and Christa Bouwman's personal website.[1]

Financial data from Call Reports covers the period between 1976 and 2016. However, my sample starts from 1984 because of missing observations for required items to construct liquidity creation measures before 1984. In addition, following Berger and Bouwman (2009), I impose the following restrictions to include only valid commercial banks in my sample. First, I exclude a bank with zero commercial real estate or commercial and industrial loans. Second, I exclude a bank with zero deposits. Third, I exclude zero or negative equity capital in the current or lagged year. Fourth, I exclude a bank whose average lagged gross total assets (GTA) are below $25 million. Fifth, I exclude a bank that has four times more unused commitments than GTA. Lastly, I exclude a bank that resembles a thrift bank or a credit card bank.[2] My final sample of almost all commercial banks in the United States from 1984 to 2007 consists of 203,711 bank-years in 1,176 state-years of data on 16,367 unique banks.

4.2 Key Dependent Variables and Independent Variables

In light of the foregoing discussion of previous literatures, I study several factors that affect my key variables. According to Berger and Bouwman (2009), the ability to securitize loans is closer to product category concept than the time until self-liquidation, and the authors also show that off-balance sheet activities provide liquidity in functionally similar ways to on-balance sheet items. Thus, I use catfat measure as a key dependent variable, as Berger and Bouwman (2009) suggest catfat is better measure than three other liquidity creation measures.

My key independent variables are proxies for bank competition. To indicate bank competition, I use the Lerner index, which is an individual measure of competition for each bank and each period. The Lerner index is commonly used in recent studies of bank competition (e.g., Fernandez de Guevara, Maudos, and Perex, 2005; Berger, Klapper, and Turk-Ariss, 2009; Jimenez, Lopez, and Saurina, 2013; Berger and Roman, 2014).

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[1] I collect the quarterly bank liquidity creation data from Christa Bouwman's personal website (http://faculty.weatherhead.case.edu/bouwman/data.html). The website provides four different quarterly bank liquidity creation measures, such as catfat, catnonfat, matfat, and matnonfat, for almost all commercial banks in the United States.

[2] I consider a bank as a thrift if the bank has residential real estate loans exceeding 50% of GTA and consider a bank as a credit card bank if the bank has consumer loans exceeding 50% of GTA.

The Lerner index is defined as the difference between price and marginal cost, divided by price, i.e., it measures the market power of a bank to set a price above marginal cost. Thus, high values of the Lerner index are associated with significant market power.

$$Lerner_{it} = \frac{Price_{it} - MC_{it}}{Price_{it}}$$

Following the methodological approach of Fernandez de Guevara, Maudos, and Perex (2005), Berger, Klapper, and Turk-Ariss (2009), and Berger and Roman (2014), I consider $Price_{it}$ as the price of GTA proxied by the ratio of total revenues to GTA for bank i at time t and MC_{it} as the marginal cost of total assets for a bank i at time t. To compute MC_{it} for each bank for each time period, I take the derivative from the following estimated translog cost function:

$$\ln(Cost_{it}) = \theta_0 + \theta_1 \ln GTA_{it} + \frac{\theta_2}{2} \ln GTA_{it}^2 + \sum_{k=1}^{3} \gamma_k \ln W_{k,it} + \sum_{k=1}^{3} \emptyset_k \ln GTA_{it} \ln W_{k,it}$$
$$+ \sum_{k=1}^{3} \sum_{j=1}^{3} \gamma_{kj} \ln W_{k,it} \ln W_{j,it} + \theta_3 Time_t + \mu_{it}$$

where i represents banks, t represents time in quarters, $Cost_{it}$ is total operating plus financial costs, GTA_{it} is gross total assets, $W_{k,it}$ represents input prices, $W_{1,it}$ is the ratio of personnel expenses to GTA, which is proxy for input price of labor, $W_{2,it}$ is the ratio of interest expenses to total deposits and money market funding, which is proxy for input price of all funds, $W_{3,it}$ is the ratio of other operating and administrative expenses to GTA, which is proxy for input price of fixed capital, and $Time_t$ is a vector of time fixed effects. The estimated coefficients of the cost function are then used to compute the marginal cost for GTA:

$$MC_{it} = \frac{Cost_{it}}{GTA_{it}} \left[\widehat{\theta_1} + \widehat{\theta_2} \ln GTA_{it} + \sum_{k=1}^{3} \widehat{\emptyset_k} \ln W_{k,it} \right]$$

I also use bank-level Herfindahl index as an alternative proxy for bank competition for the robustness check. To measure the bank-level HHI, I establish the Herfindahl index of the markets in which the bank has deposits and then weight these market indices by the proportion of the bank's deposits in each of these markets. I use the natural logarithm of the HHI to avoid distorting the regression analyses due to large values.

Using Lerner Index as a proxy for bank competition, I examine the relation between bank competition and bank liquidity creation, but I cannot claim causal relation because of endogeneity concerns, such as omitted variables and reverse causality problems. To mitigate the endogeneity concerns, I exploit exogenous variations in bank competition through the U.S. bank deregulation events, such as intra- and interstate bank deregulation and interstate bank branching deregulation. Following previous studies exploiting bank deregulation events (e.g., Jayaratne and Strahan, 1996; Black and Strahan, 2002; Johnson and Rice, 2008; Rice and Strahan, 2010; Krishnan, Nandy, and Puri, 2014), I construct intra- and interstate deregulation indicator variables, Rice-Strahan index, and Krishnan-Nandy-Puri index.

The intra- and interstate deregulation indicator variables take the value of one from the year of deregulation onward and zero prior to the deregulation. Rice-Strahan index of interstate banking deregulation ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state. On the other hand, Krishnan-Nandy-Puri index ranges from one (highly regulated) to five (deregulated).

4.3 Control variables

To investigate clear relations between bank competition and bank liquidity creation, I include some control variables that influence bank liquidity created by banks. Following Berger and Bouwman (2009), I include a group of bank-level variables. To capture the risk, I include equity capital ratio, which is the ratio of equity to GTA, and Z-Score, which is the distance to default that measured as the bank's return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets, as a proxy for credit risk. In addition to the ZSCORE, I include earnings volatility, which is measured as the standard deviation of the bank's return on assets over the previous twelve (minimum: eight) quarters. I also control for the bank's multibank holding company (MBHC) status because banks of multibank holding company could have much more sufficient resources that can potentially affect bank liquidity creation strategy. Furthermore, I control for the bank's merger and acquisition history because banks often substantially alter their lending behavior following mergers and acquisitions.

Different from Berger and Bouwman (2009), I do not include bank size, market share, and a bank-level Herfindahl index as control variables in specifications using Lerner Index as a proxy for bank competition because these variables are strongly related to Lerner index, which is an indicator for bank competition. However, I control for bank size when I use bank deregulation variables as a proxy for bank competition. To control for macroeconomic condition of local markets in bank-level analysis, I control for natural logarithm of state population, Housing Price Index (HPI), natural logarithm of personal income, and GDP per capita.

For state-level analysis, I control for local market macroeconomic conditions, such as natural logarithm of state population, Housing Price Index (HPI), natural logarithm of personal income, GDP per capita, Ln(Population), HPI, State deposit per capita, State equity per capita, Number of potential borrowers, and Number of competitors.

Lastly, I include year fixed effects, firm fixed effects, state fixed effects, and state-year fixed effects in various specifications in this paper to control for time-specific effects, individual firm specific effects, state-specific effects, and state-level trends, respectively. In this paper, I do not report results including state-fixed effects because state fixed effects are almost nested within bank fixed effects and the results are consistent with specifications including bank fixed effects.

4.4 Models

To investigate the impact of bank competition on bank liquidity creation and test hypotheses, I estimate following equations:

$$\text{Liquidity}_{ijt} = \alpha_i + \alpha_t + \beta_0 + \beta_1\text{Lerner}_{ijt-1} + \gamma\text{Control}_{ijt-1} + \varepsilon_{ijt} \qquad (1)$$

where i indexes banks, j indexes state of the banks, t indexes year, and α_i and α_t are bank fixed and year fixed effects, respectively.

As I discussed in 4.3, the key dependent variable is the dollar amount of liquidity a bank has created normalized by GTA, using catfat measure from Berger and Bouwman (2009) and the key explanatory variable is the lagged Lerner Index, which is a popular proxy for market power, and control variables that could affect the bank liquidity creation are included. I use the lagged values for independent variables and employ the fixed effects model to mitigate the endogeneity of the measures of bank competition and to avoid biased results because fixed effect model control a problem that biased results might be yielded because of unobserved individual characteristics if I regress without fixed effect model and the fixed effect model is more robust to endogeneity. Year fixed effects control for the time trend such as a set of macroeconomic condition including inflation. In the equation, μ_i means each bank's individual specific effect, and ν_t means that time specific effect. Liquidity_{it} is the dollar amount of liquidity a bank has created normalized by GTA, Lerner_{it-1} is the lagged Lerner Index, $Control_{it-1}$ is a set of control variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. All regressions are estimated with robust standard errors, clustered by bank, to control for heteroskedasticity, as well as possible correlation among observations of the same bank in different years.

To mitigate the endogeneity concerns, I also employ a difference-in-differences estimator. Using the proportion of state-level bank liquidity creation, we investigate whether banks differently react to change in bank competition. Banks would decide their liquidity creation decisions strategically in response to different level of supply-side competition in different states. Some banks would prefer to focus on less competitive market to easily dominate the market as early as possible and to enjoy the stable life. However, the other banks would prefer to compete in competitive market to keep their competitive positions in the market and to expand their territories.

Bank deregulation ignites bank competition and reallocates assets to more competitive banks. Thus, it affects bank competition at the beginning of the deregulation. As Jayaratne and Strahan (1997) suggest that banking deregulation affects not credit supply but bank competition, using the staggered banking deregulation events as exogenous shocks allows us to exploit the exogenous variation in bank competition. It mitigates potential endogeneity concerns. Following several previous studies using the bank deregulation (e.g., Johnson and Rice, 2008; Rice and Strahan, 2010; Koetter, Kolari, and Spierdijk, 2012; Chava, Oettl, Subramanian, and Subramanian, 2013; Krishnan, Nandy, and Puri, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015), I use a difference-in-differences approach to examine a causal effect of bank competition on bank liquidity creation after a change in bank branching regulation.

$$\text{Liquidity}_{ijt} = \alpha_i + \alpha_t + \gamma\text{Control}_{ijt} + \delta Deregulation_{jt} + \varepsilon_{ijt} \ (2)$$

where i indexes banks, j indexes state of the banks, t indexes year, Liquidity_{it} is the key dependent variable of interest, and α_i and α_t are firm fixed and year fixed effects, respectively. $Control_{ijt}$ is a set of control variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. $Deregulation_{jt}$ includes intra- and interstate bank deregulation indicator variables and interstate bank branching deregulation variables. This methodology fully controls for fixed differences between treated and control banks via the bank fixed effects. Also, year fixed effects for aggregate fluctuations. δ is estimate of the banking deregulation effects. All regressions are estimated with robust standard errors, clustered by state, to control for heteroskedasticity, as well as to allow for an arbitrary serial correlation within state over time because bank deregulation variables vary at the state level.

To examine the effects of state-level bank competition on state-level bank liquidity creation, I estimate a following equation:

$$\text{State Liquidity}_{jt} = \alpha_j + \alpha_t + \gamma\text{Control}_{jt} + \delta Deregulation_{jt} + \varepsilon_{jt} \ (2)$$

where j indexes state, t indexes year, State Liquidity_{jt} is the key dependent variable of interest, and α_j and α_t are state fixed and year fixed effects, respectively. $Control_{jt}$ is a set of state-level macroeconomic variables, and ε_{it} is an error term, which assumes that $E(\varepsilon_{it})=0$ and $Var(\varepsilon_{it})=\sigma^2$. $Deregulation_{jt}$ includes intra- and interstate bank deregulation indicator variables and interstate bank branching deregulation variables.

[Table 1: Summary Statistics]

Panels A and B of Table 1 report summary statistics for all sample banks, large banks, small banks, and the difference in summary statistics between large banks and small banks. I divide sample banks into three groups by size. I define a bank as a large bank if its gross total assets (GTA) exceed \$3 billion. If a bank's GTA is between \$1 billion and \$3 billion, then I define the bank as a medium bank. Lastly, the other sample banks whose GTA is up to $1 billion are considered as small banks. I have 16,367 unique sample banks for the sample period between 1984 and 2007. Among the sample banks, numbers of banks that are categorized as large banks and medium banks at least once are only 563 and 1,184 respectively. It is only 10% of total sample banks. This means that approximately 90% of the sample banks are small banks in this setting.

From Panel B of Table 1, we can also see that there are highly statistically significant differences between small banks and medium/large banks for all liquidity creation behavior and bank characteristic variables. This suggests that there is substantial heterogeneity between small banks and medium/large banks for the perspective of both liquidity creation behaviors and bank characteristics.

5. Empirical Results

5.1 The effect of bank competition on bank liquidity creation

This section describes the effect of bank competition on bank liquidity creation. In this section, I examine the relationship between bank competition and bank liquidity creation. Using Lerner index as a proxy for bank competition and catfat measure, which is scaled by gross total assets, as a proxy for bank-level liquidity creation, I investigate how bank-level strategy for liquidity creation is affected by the ex-ante extent of bank competition. My analysis includes controls for a wide range of variables that could affect bank liquidity creation as mentioned in Section 4.

[Table 2: Base regressions]

Table 2 presents ordinary least squares (OLS) estimates of the relationship between bank competition and bank liquidity creation. All independent variables are lagged. Columns (1) and (3) of Table 2 include both bank fixed effects and time fixed effects, and Columns (2) and (4) include both bank fixed effects and state-specific time trend fixed effects. Also, all specifications are estimated with robust standard errors, clustered by bank, to control for heteroskedasticity, as well as possible correlation among observations of the same bank in different years.

In Table 2, I find a statistically and economically significant inverse relationship between bank competition and bank liquidity creation. Because higher value of Lerner Index implies greater market power, this means that banks with greater market power would create more liquidity in the market. The result remains significant even after I control for bank characteristics and state-level macroeconomic conditions. This shows that an increase of one standard deviation in Lerner Index is related to 8.7% increase of a standard deviation in bank liquidity creation. To control for state-specific time trend, such as regulatory changes, I include state-year fixed effects instead of year fixed effects in Columns (2) and (4). The inverse relation between bank competition and liquidity creation is still held. However, the results from Table 2 do not explain what types of banks dominate this effect and which component of bank liquidity creation is more correlated with the bank competition.

Now, to investigate these parts, I present the findings for different categories of banks. First sub-sample analysis is for small, medium, and large banks. Second sub-sample analysis is for sub-components of liquidity creation, such as asset-side liquidity creation, liability-side liquidity creation, and off-balance sheet liquidity creation.

[Table 3: Sub-sample regressions (Size)]

In Table 3, which contains sub-sample analyses by bank size, I find that small banks and medium and large banks react differently as Lerner Index increases. Columns (1) and (2) show the results for small banks, Columns (3) and (4) show the results for medium banks, and Columns (5) and (6) show the results for large banks. Columns (1), (3), and (5) include bank fixed effects and year fixed effects. On the other hand, Columns (2), (4), and (6) control for time invariant bank specific characteristics and state-specific time trend. Table 3 shows that statistically significant and positive coefficients on Lerner Index in Table 2 are strongly driven by small banks. The coefficients on Lerner Index for medium and large banks are statistically insignificant. That is, I find that only small banks create more liquidity in the market as bank competition decreases. The results show that medium and large banks' liquidity creation strategies would not be significantly correlated with bank competition.

As I discuss in section 2, these results suggest that small banks create more liquidity when the market is concentrated because their resources are relatively focusing on the market and they do want to utilize their own private information about their customers by keeping the relationship with the borrowers. On the other hand, in the concentrated market, large banks would prefer to pursue monopolistic gains, such as higher interest rate and lower deposit rate. Since they have sufficient resources to overcome reduced demand of borrowers and unexpected financial shocks for a while until the borrowers inevitably take the bad deals, they could respond to bank competition differently. In Columns (2), (4), and (6) of Table 3, we can see that the coefficients on Lerner Index is quite similar to the coefficients on Lerner Index when I control for bank fixed effects and year fixed effects. This means that differential time trends in bank liquidity creation across states are correlated with bank competition but the omitted variable bias regarding state-specific time trend is not significant.

[Table 4: Sub-sample regressions (Components of BLC)]

In Table 4, I examine the relation between bank competition and three different components of bank liquidity creation, including asset-side, liability-side, and off-balance sheet liquidity creation. Table 4 shows that positive and statistically significant relation between Lerner Index and bank liquidity creation is only driven by asset-side liquidity creation. For the perspective economic significance, the result in Column (3) means that an increase of one standard deviation in Lerner Index causes 2.9% increase of a standard deviation in asset-side liquidity creation. The results suggest that banks in less competitive market create more liquidity only through asset-side, such as commercial and industrial loans, real estate loans, and so on. This result is consistent with the evidence that the positive correlation between bank competition and liquidity creation is driven by small banks. This is because small banks are more focusing on asset-side liquidity creation activities than large banks and off-the-balance sheet activities are mostly occurred in large banks. The specifications in Columns (2), (4), (6), (8), (10), and (12) include state-time trend fixed effects. From the columns containing state-time trend, we can see that the estimates are not affected by state-specific trends because the coefficients remain stable.

I conclude that banks create less liquidity in the competitive market. To be specific, this relation is driven by small banks and asset-side liquidity creation activities. The results suggest that banks react differently to change in market competition structure and have heterogenous liquidity creation strategies. In this section, I investigate the relation between bank competition and liquidity creation and do not claim causal conclusions from my analysis. In following section, I exploit the U.S. bank deregulation events to mitigate endogeneity concerns.

5.2 The effects of bank deregulation on bank liquidity creation

In this section, I examine the effects of bank deregulation on bank liquidity creation. Previous studies suggest that bank deregulation facilitates bank competition and reallocates assets to more competitive banks. Thus, as Jayaratne and Strahan (1996) suggest that banking deregulation affects not credit supply but bank competition, using the staggered banking deregulation events as exogenous shocks allows us to exploit the exogenous variation in bank competition. It mitigates potential endogeneity concerns. Following several previous studies using the bank deregulation (e.g., Koetter, Kolari, and Spierdijk, 2012; Chava, Oettl, Subramanian, and Subramanian, 2013), I use a difference-in-differences approach to examine a causal effect of bank competition on bank liquidity creation after a change in both intra- and interstate bank regulation. Table 5 shows base regressions examining the effects of intra- and interstate banking deregulation events on bank liquidity creation.

[Table 5: Effects of Bank Deregulation on Bank Liquidity Creation]

Using both intrastate and interstate bank deregulation events as exogenous shocks, I find that exogenous variations in bank competition after both intra- and interstate deregulation events do not significantly affect bank liquidity creation. This could be because of fixed costs to invest in deregulated states. Because interstate deregulation requires much higher fixed costs to invest in deregulated states, only sizable banks are able to acquire and/or establish a charter in a state outside the main bank's home state. On the other hand, small banks would not compete with the sizable competitors. That is why these two effects could offset each other. In addition, existing large banks in the deregulated state could have chance to invest in the other deregulated states. This could also affect the insignificant effects of interstate deregulation.

Different from previous studies examining the effects of bank deregulation, results in Table 5 show that intrastate deregulation and interstate deregulation have resembling effects on bank liquidity creation on average. To disentangle the effects, I examine sub-sample analysis by bank size in Table 6.

[Table 6: Effects of Bank Deregulation on Bank Liquidity Creation: Size]

Columns (1) – (3) show the results of sub-sample analysis and Columns (4) – (6) show the results of specifications including interaction terms between bank size dummy variables and bank deregulation variables. In Column (1), I find positive but insignificant effects of interstate deregulation on bank liquidity creation. We can see that the result in Column (1) of Table 5 is driven by small banks and fixed cost channel. From Columns (2) and (3), we can see that there are positive and slightly significant effects of interstate deregulation on medium and large banks' liquidity creation. These results suggest that banks that have more sufficient resources either to invest in the deregulated market or to compete with newcomers from outside the state create more liquidity after the interstate bank deregulation.

To identify relative effects of bank size, I include interaction terms in Column (4) – (6). Consistent with previous studies, I find that intrastate deregulation and interstate deregulation have contrasting effects on bank liquidity creation. Small banks in states that passed intrastate bank deregulation create more liquidity in the market but the small banks in states that passed interstate bank deregulation create less liquidity in the market than the other sized banks. On the other hand, large banks create less liquidity after intrastate deregulation but create more liquidity after interstate deregulation. This is because of characteristics of competitors.

For the intrastate competition, competitors are limited, and banks are aware of their intrastate competitors. That is why small banks could create more liquidity to keep their relationship with current customers and large banks could create less liquidity to enjoy monopolistic rents. However, for the interstate competition, banks in the deregulated states would not have sufficient information about potential competitors. Small banks would not have ample resources to compete with incoming out-of-state banks, but large banks would have sufficient resources to dominate the market even after interstate deregulation. That is why small banks would create relatively less liquidity creation in the market than larger banks to avoid default risk and larger banks would create more liquidity to dominate the market.

For the perspective of out-of-state banks, they would not want to compete with large banks operating in the deregulated states because there is little chance to dominate the market over the large local banks. That is why large banks might not need to create more liquidity after interstate deregulation on average. This could explain positive but statistically insignificant coefficient on interaction term between large bank dummy and interstate deregulation.

5.3 The effects of interstate branching deregulation on bank liquidity creation

In this section, to mitigate endogeneity concerns, I exploit the staggered interstate bank branching deregulation. In 1994, the Interstate Banking and Branching Efficiency Act (IBBEA) is passed and the IBBEA is implemented in 1997 to allow interstate branching. However, the U.S. government gives state governments authorities to regulate interstate branching. State governments can either create or relax interstate bank branching restrictions.

As Johnson and Rice (2008) and Rice and Strahan (2010) state, interstate bank branching deregulation is more important than intra- and interstate bank deregulation regarding bank competition and credit supply. This is because loan contracts and deposit contracts are accomplished at the branch-level. To measure interstate branching deregulation, I follow previous seminal papers, such as Johnson and Rice (2008), Rice and Strahan (2010), and Krishnan, Nandy, and Puri (2014). I mainly use Rice and Strahan Index and use Krishnan, Nandy, and Puri Index for the robustness checks.

The Interstate Banking and Branching Efficiency Act (IBBEA) allows state governments to erect barriers to entry. According to Johnson and Rice (2008) and Rice and Strahan (2010), there are four specific restriction on interstate bank branching. Based on the four restrictions, they construct Rice and Strahan Index (RSI, thereafter). I add one to the RSI when a state adds any of barriers to entry. Thus, maximum value of RSI is four, which indicates the states are the most restrictive to interstate bank branching and minimum value of RSI is zero, which indicates the states are the most open to interstate bank branching. First restriction is the minimum age of the target banks. States could impose a minimum age of 3 or more years on target banks of interstate branch acquirers. A maximum age restriction is 5 years. Second restriction is de novo interstate branching. I add one to RSI if states do not allow de novo interstate branching. Third restriction is the acquisition of individual branches. To weaken excessive external acquisitions, deregulated states could require an out-of-state bidder bank to acquire all branches of its target bank. I add one to RSI if states do not allow individual branch acquisition. Last restriction is a statewide deposit cap. The IBBEA has a provision about deposit concentration, which is 30%. However, state governments still have authorities to build a higher or lower entry barrier regarding deposit cap, which is the maximum amount of deposits that a single bank can hold. Thus, I add one if states set the deposit cap less than 30%.

Krishnan, Nandy, and Puri (2014) add one more restriction to RSI. Krishnan, Nandy, and Puri Index (KNP, thereafter) includes four restrictions that RSI already has and an additional restriction, which is reciprocal requirement. This requirement means that interstate branching is allowed only if a state where an out-of-state bank want to enter, and a home state of the out-of-state bank permit the same level of interstate branching. Different from RSI, value of KNP index increases as the state relax restrictions. Thus, maximum value of KNP index is five, which indicates the states are the most open to interstate bank branching. This index takes the value zero for all years before the implementation of interstate bank branching deregulation.

[Table 7: Effects of Interstate Branching Deregulation on Liquidity Creation]

[Table 8: Effects of Interstate Branching Deregulation on Liquidity Creation by bank size]

Table 7 reports the results of fixed effects regressions examining the effects of interstate branching deregulation on bank liquidity creation. The coefficient estimates of RSI are positive and significant at the 1% level on average. This finding suggests that an increase in banking competition due to bank branching deregulation (i.e., a decrease in RSI) leads to a decrease in bank liquidity creation. To be specific, based on the coefficient of RSI in column (3) of Table 7, states that are completely open to interstate branching generated a total of 1.55% (=4×0.00388) less liquidity creation after interstate bank branching deregulation than states with the most restrictions on interstate branching after deregulation. I find robust evidence when I use KNP index instead of RSI index. The results suggest that interstate bank branching deregulation causes statistically significant effects on bank-level liquidity creation, but economic significance is not substantial.

The results in Table 7 are surprising. This is because I find contrasting effects of interstate bank deregulation on bank liquidity creation. Both interstate deregulation and interstate branching deregulation exogenously increase bank competition, but the effects are different. This could be explained by

Interstate deregulation allows out-of-state banks to acquire banks in deregulated states, but interstate branching deregulation allows out-of-state banks to acquire or establish branches in deregulated states. This means that there will be much higher fixed costs that incoming banks must pay in the case of interstate deregulation. As we can see from findings in Table 6, the higher fixed costs could be a role of an entry barrier, so relatively large banks are more likely to enter the new market, which is the deregulated state. Thus, both newcomers and existing medium and large banks in the deregulated banks would create more liquidity to compete each other.

However, interstate branching deregulation lowers the fixed costs to enter new markets. That is why existing banks in the most restrictive states could choose to invest in the other open markets. For example, a bank in the most restrictive states could establish or acquire a branch at neighboring states if the fixed cost for setting up a new branch in the adjacent states is much lower than expected returns of the investment and/or the fixed cost for expanding a business within its home state. This could be possible explanation about the conflicting effects of interstate deregulation and interstate branching deregulation.

Table 8 reports the results of subsample analysis by bank size. This examines whether the effects of interstate branching deregulation on liquidity creation vary in different bank size. In the competitive market, small banks tend to create more liquidity than medium/large banks to avoid bank failure. On the other hand, large banks create even less liquidity than medium/small banks because they are more likely to be a dominant player in the market and they prefer to enjoy monopolistic rents. These results are robust to controlling for bank characteristics, macroeconomic conditions, banking deregulatory events that precede the IBBEA, bank fixed effects, and year fixed effects.

5.4 The effects of bank deregulation on state-level bank liquidity creation

In previous sections, I examine the effects of bank competition on bank-level liquidity creation. Understanding the effects of bank competition on bank-level liquidity creation is interesting and important but the effects state-level bank competition on aggregate state-level bank liquidity creation would be much more important because government policies are generally established at the state-level. In this section, using bank deregulation events, including intra- and interstate bank deregulation and interstate bank branching deregulation, I examine whether state-level bank competition affects state-level bank liquidity creation.

Following Berger and Sedunov (2017), I define state-level bank liquidity creation as aggregate deposit of the state normalized by population of the state. To estimate state-level catfat measure, I firstly construct each bank's bank-state level market share using state-level deposit data from FDIC. By multiplying the bank-state level market share by each bank's liquidity creation measures, I can estimate bank-state level liquidity creation. For example, suppose Bank of America's total deposit in 2006 is $35 million and Florida branches have $10 million of deposit, South Carolina branches have $5 million of deposit, and Texas branches have $20 million of deposit. We can see that Bank of America's market share in Florida is 28.57% (= $10 million/$35 million). If the value of catfat for Bank of America in 2006 is $100 million, then we can assume that Bank of America creates $28.57 million in Florida at that time. After calculating the bank-state level liquidity creation, I combine all bank-state level liquidity creation by state. Lastly, I normalize the aggregate state-level bank liquidity creation by state population, which is collected from the U.S. Bureau of Economic Analysis (BEA).

State-level control variables are collected from Call Report, U.S. Bureau of Economic Analysis (BEA), and Federal Housing Finance Agency (FHFA). State-level control variables include natural logarithm of state population, GDP per capita, state personal income per capita, house price index (HPI), total state deposit per capita, state book equity per capita, and inflation. Also, state and year fixed effects are included in all specifications.

[Table 9: Effects of Intra- and Interstate Deregulation on State-level Liquidity Creation]

Table 9 reports the results of regressions examining the effects of intra- and interstate bank deregulation on state-bank liquidity creation per capita. I find that there is no statistically significant empirical evidence that intra- and interstate bank deregulation events affect state-level bank liquidity creation. Because bank deregulation stimulates bank competition and its objective is to enhance financing condition of the market, this result is meaningful. The results suggest that intra- and interstate bank deregulation policy did not play an appropriate role to encourage banks' liquidity creation incentives. Based on empirical results in previous tables, one possible explanation is that the effects of bank deregulation events on large banks and on small banks offset each other. This suggests that the policy, that is applied to all heterogenous banks in the same way, does not fit all.

[Table 10: Effects of Intra- and Interstate Deregulation on State-level Liquidity Creation by Size]

Berger and Sedunov (2017) find that small bank liquidity creation is more important than large bank liquidity creation for the perspective of per dollar effects. This could be because small banks are more focused on small firm finance, which is important to local market growth, than large banks. Different from small-sized borrowers, large firms have more options to raise funds and they would prefer large lenders because of large banks have much sufficient resources and have much lower default risk than small banks.

In Table 10, I examine whether bank deregulation events affect state-level small bank liquidity creation and large bank liquidity creation differently. I find no statistically significant evidence that bank deregulation events affect state-level small bank and/or large bank liquidity creation. In Columns (4) – (6) and (10) – (12) of Table 10, I also find that the results are robust to including state-level macroeconomic variables.

As I discussed in section 5.3, interstate bank branching deregulation would be much more important in bank liquidity creation than bank deregulation events occurred in 1970s and 1980s. Because loan and deposit decisions, which are major drivers of on-balance sheet liquidity creation, are generally made at branch-level, interstate bank branching deregulation would have more direct and significant effects on bank liquidity creation.

[Table 11: Effects of Bank Branching Deregulation on State-Level Bank Liquidity Creation]

Table 11 presents the results of state-level analysis examining the effects of interstate branching deregulation on aggregate state-level liquidity creation per capita. Consistent with previous results of intra- and interstate bank deregulation, I find no significant empirical evidence. This suggests that, on average, even interstate bank branching deregulation does not affect state-level bank liquidity creation per capita. The result is robust to a variety of alternative proxies for interstate bank branching deregulation, such as KNP Index.

[Table 12: Effects of Bank Branching Deregulation on State-Level Small/Large Bank LC]

However, different from analyses using intra- and interstate bank deregulation, I find significantly different effects of interstate bank branching deregulation on small bank and large bank liquidity creation. Table 12 reports that enhanced bank competition caused by interstate bank branching deregulation leads to less liquidity per capita created by small banks in the market. Based on the coefficient of RS Index in Column (2) of Table 12, we can see that the result is economically significant as well. On the other hand, I find no significant effects on large bank liquidity creation. Because large banks create more liquidity in terms of dollar values and small banks are reluctant to create liquidity in the competitive market, the results support the view that large banks enjoy monopolistic rents if they are dominant players. The results are robust if I use alternative measures of interstate bank branching deregulation. The results suggest that interstate bank branching deregulation result in even worse local market liquidity condition because small bank liquidity creation is crucial channel for local market growth (e.g., Berger and Sedunov, 2017).

The results of state-level analyses provide an important policy implication. The objective of bank deregulation is to encourage local market economy and a crucial channel that banks can contribute to local market economic growth is bank liquidity creation. Even though Jayaratne and Strahan (1996) find that the relaxation of bank branching restrictions positively affects local market economic growth, my results suggest that the positive effects might not be driven by bank-oriented effects, which is bank liquidity creation. Thus, the policy implication of the state-level results is that the government policy regarding bank competition need to consider banks' heterogeneity, such as bank size and bank market share, and markets' heterogeneity, such as market demand and supply-side competition status.

5.5 Additional robustness tests

Results in state-level analyses support the implication that a policy to encourage bank competition would be more efficient if the policy applies to banks depending on banks' heterogeneity, such as bank size and bank market share, and markets' heterogeneity, such as market demand and supply-side competition status prior to the policy implementation.

One concern about state-level analysis is a definition of state-level bank liquidity creation. Because there is no available branch-level financial and accounting data except branch-level deposit data, I only rely on deposit market share to calculate weights for each state when I construct state-level liquidity creation. Deposit market share would be closely related to bank's concentration on the market but there is a potential measurement error issue. To mitigate this concern, I use DealScan data to construct a partial measure of state-level bank liquidity creation. DealScan data provides information about borrower's location and total loan amount so I use the information to calculate more accurate state-level liquidity creation weights. Even though loan creation is a part of bank liquidity creation, which is a part of asset-side liquidity creation, using DealScan data allows me to identify correct weights for each state where a bank operates. Table 13 shows results of state-level analyses using DealScan data are consistent with previous results using state-level bank liquidity creation relying on deposit market shares. This suggests that main state-level liquidity creation measures in this paper are valid.

In untabulated tests, I conduct several additional robustness checks. Firstly, to resolve a concern about any potential bias on bank competition measure, I run identical tests using different explanatory variables. As I mentioned in previous sections, one of key independent variables of this paper is Lerner Index, which is a proxy for bank competition (i.e. bank market power). As banking literature widely uses Herfindahl-Hirschman Index as one of the proxy for bank competition or bank concentration, I explore same specification with Herfindahl-Hirschman Index instead of Lerner Index. Results are generally consistent with the results using Lerner Index.

In addition, I use a different comprehensive liquidity creation measure, matfat, instead of catfat. As I discuss in Section 2, only difference between catfat and matfat measures is a way to classify loans. Catfat measure classifies loans by category but matfat measure classifies loans by maturity. It will be ideal if I can consider both category and maturity when I classify the loans. Unfortunately, lack of available data does not allow us to consider both ways. Because category-based classification captures loan-specific characteristics, Berger and Bouwman (2009) suggest that catfat measure is the most comprehensive measure of bank liquidity creation among their four liquidity creation measures. However, maturity-based classification would be essential when I compare same kinds of loans. Thus, there is a possibility that maturity-based classification has a merit to evaluate loan-side liquidity creation. Thus, I run the identical tests using the matfat measure as a robustness check. The results are still consistent.

6. Conclusion and Discussion

Banks' role as liquidity creators is crucial for local market condition and economic growth. However, the determinants of bank liquidity creation are understudied. While a large literature suggests that bank competition affects local market economic growth, it is unclear whether bank-side liquidity creation is a major economic channel of the effects of bank competition on economic outputs. Empirical evidence of this paper suggests that the effects of bank competition on economic growth would not originate from bank-side liquidity creation channel.

From bank-level analysis, I find that bank competition affects bank-level liquidity creation behavior. I also find that staggered interstate bank branching deregulation, which represents an exogenous variation in bank competition, affects bank-level liquidity creation.

Different from bank-level analysis, state-level analysis shows that bank deregulation events do not significantly affect state-level bank liquidity creation on average. Additional analysis regarding in-state banks' liquidity creation and out-of-state banks' liquidity creation shows that the effects of bank competition offset each other. Also, I find that bank competition affects differently small/medium bank liquidity creation and large bank liquidity creation. These effects offset each other as well. The results suggest that the policy, that is applied to all heterogenous banks in the same way, does not fit all. It highlights the role of proper regulation to encourage depressed credit market.

There are some points I can develop deeper. Firstly, the U.S. government implemented TARP program after the recent financial crisis to encourage credit supply, so it will be interesting to use TARP as an exogenous shock on market power. Even though this is not purely random, it is worth to exploit the exogenous variation in market power.

According to Bayazitova and Shivdasani (2012) and Duchin and Sosyura (2014), there are some banks that received TARP fund offer but withdrew the offer. Collecting data for these qualified but non-TARP recipients would allow me cleaner tests. Even though it would be quite small sample analysis, comparing this group with TARP recipients would be cleaner test than comparing TARP recipients and non-recipients. This further analysis could provide additional evidence whether government achieved its expected results of the government intervention or bank managers took excessive risks at the expense of the government, following theoretical models of bank risk-taking.

REFERENCES

Beck, T., Demirguc-Kunt, A., & Maksimovic, V. (2004). Bank competition and access to finance: International evidence. *Journal of Money, Credit, and Banking*, *36*(3), 627-648.

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*(9), 3779-3837.

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. Journal of Financial Services Research, 35(2), 99-118.

Berger, A. N., & Roman, R. A. (2013). Did TARP banks get competitive advantages? University of South Carolina working paper.

Berger, A. N., & Sedunov, J. (2017). Bank liquidity creation and real economic output. *Journal of Banking & Finance*, *81*, 1-19.

Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of finance*, *60*(3), 1329-1343.

Boyd, J. H., De Nicolò, G., & Jalal, A. M. (2006). Bank risk-taking and competition revisited [electronic resource]: new theory and new evidence. *International Monetary Fund.*

Boyd, J. H., De Nicolò, G., & Jalal, A. M. (2009). Bank competition, risk and asset allocations (No. 2009-2143). *International Monetary Fund.*

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking & Finance*, *4*(4), 335-344.

Carbó-Valverde, S., Rodriguez-Fernandez, F., & Udell, G. F. (2009). Bank Market Power and SME Financing Constraints*. *Review of Finance*, *13*(2), 309-340.

De Guevara, J. F., Maudos, J., & Perez, F. (2005). Market power in European banking sectors. *Journal of Financial Services Research*, 27(2), 109-137.

Deep, A., & Schaefer, G. (2004). Are banks liquidity transformers? (No. rwp04-022).

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *The journal of political economy*, 401-419.

Gatev, E., & Strahan, P. E. (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The Journal of Finance*, *61*(2), 867-892.

Gorton, G., & Pennacchi, G. (1990). Financial intermediaries and liquidity creation. *The Journal of Finance*, *45*(1), 49-71.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American economic review*, 147-165.

Holmstrom, B., & Tirole, J. (1996). Private and public supply of liquidity (No. w5817). National Bureau of Economic Research.

Horvath, R., Seidler, J., & Weill, L. (2013). How bank competition influence liquidity creation (No. 16/2013). Bank of Finland, Institute for Economies in Transition

Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial economics*, 97(3), 319-338.

Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, *111*(3), 639-670.

Jiang, L., Levine, R., & Lin, C. (2016). Competition and bank liquidity creation (No. w22195). National Bureau of Economic Research.

Joh, S. W., & Kim, J. (2008). Does Competition Affect the Role of Banks as Liquidity Providers? *Seoul National University*.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, 9(2), 185-195.

Kashyap, A. K., Rajan, R., & Stein, J. C. (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance*, *57*(1), 33-73.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American economic review*, *80*(5), 1183-1200.

Love, I., & Martínez Peria, M. S. (2012). How bank competition affects firms' access to finance.

Marcus, A. J. (1984). Deregulation and bank financial policy. *Journal of Banking & Finance*, *8*(4), 557-565.

Nicoló, D., De Nicol, G., & Loukoianova, E. (2007). *Bank ownership, market structure and risk*. International Monetary Fund.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The journal of finance*, *49*(1), 3-37.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, *110*(2), 407-443.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. *Journal of financial Intermediation*, *13*(2), 156-182.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, *41*(4), 711-734.

Table 1: Summary Statistics

This table contains summary statistics for all sample banks and contains summary statistics that compare small banks with medium/large banks. The sample comprises 16,367 unique commercial banks over the period 1984 to 2007. Panel A presents bank -level descriptive statistics for the full sample. Panel B presents univariate differences between small banks versus medium/large banks. Each bank is categorized by size based on its gross total assets (GTA). Gross total assets (GTA) is total assets + the allowance for loan and lease losses + the allocated transfer risk reserve (a reserve for certain foreign loans). A bank is classified as a large bank if its GTA are exceeding \$3 billion, as a medium bank if its GTA are between \$1 billion and \$3 billion, and as a small bank if its GTA are below \$1 billion. Panel C shows state-level descriptive statistics. All financial values are measured in real 2007 dollars using the implicit GDP price deflator. The table reports number of observations, sample means, and standard deviations. For liquidity creation measures, catfat is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities. catnonfat is a category-based liquidity creation measure, including only on-balance sheet activities. lc_a, lc_l, and lc_obs are asset-side liquidity creation, liability-side liquidity creation, and off-the-balance sheet liquidity creation, respectively. Liquidity creation variables with a "gta" suffix are liquidity creation measures normalized by GTA. Lerner Index is the observed price-cost margin divided by price. Equity Ratio is total equity capital divided by GTA. Bank Size is Natural log of GTA. Earnings Volatility is standard deviation of the bank's quarterly return on assets measured over the previous twelve quarters, multiplied by 100. ZSCORE is the bank's return on assets plus the equity capital/GTA ratio divided by the standard deviation of the return on assets. Multi-BHC is an indicator variable, which is equal to 1 if the bank has been part of a multibank holding company over the past three years. Acquisitions is an indicator variable, which is equal to 1 if the bank was acquired in the last three years. INTRA is an indicator variable, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation. INTER is an indicator variable, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. RS Index is Rice-Strahan index of interstate banking deregulation. It ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state. KNP Index is Krishnan-Nandy-Puri index. It ranges from one (highly regulated) to five (deregulated). GDP is state-level gross domestic production. Personal Income is state-level personal income level. HPI is state-level housing price index. In Panel C, state-level variables with a "per capita" suffix are variables normalized by state population.

Panel A: Summary Statistics (Bank-level)

	N	Mean	SD
Liquidity Creation Variables			
catfat	206,198	267,479	4,728,000
catnonfat	206,198	130,205	1,728,000
lc_a	206,198	27,485	667,700
lc_l	206,198	102,720	1,388,000
lc_obs	206,198	137,274	3,576,000
catfat_gta	206,198	0.201	0.194
catnonfat_gta	206,198	0.160	0.150
lc_a_gta	206,198	-0.0151	0.138
lc_l_gta	206,198	0.175	0.0651
lc_obs_gta	206,198	0.0406	0.0958
Bank-level Variables			
Lerner Index	203,711	0.315	0.109
Equity Ratio	205,097	0.0939	0.0421
Gross Total Assets	205,100	537,878	7,602,000
Bank Size	205,315	11.61	1.150
Earnings Volatility	203,011	0.00448	0.00360
ZSCORE	193,588	47.68	53.39
Small Bank	206,198	0.953	0.212
Medium Bank	206,198	0.0269	0.162
Large Bank	206,198	0.0201	0.140
Multi-BHC	206,198	0.254	0.435
Acquisitions	206,198	0.0777	0.268
State-level Bank Deregulation Variables			
INTRA	206,198	0.779	0.415
INTER	206,198	0.837	0.369
RS Index (4 Restrictions)	206,198	3.423	1.152
KNP Index (5 Restrictions)	206,198	1.231	1.704
KNP Index (4 Restrictions)	206,198	0.968	1.506

Table 1: Summary Statistics

Panel B: t-test (Small Banks vs. Large/Medium Banks)

	Small Banks			Large and Medium Banks			t-test	
	N	Mean	SD	N	Mean	SD	Difference	p-value
Liquidity Creation Variables								
catfat	196,500	34,426	63,416	9,698	4,990,000	21,260,000	4,955,574	0.0000
catnonfat	196,500	27,381	48,484	9,698	2,214,000	7,676,000	2,186,619	0.0000
lc_a	196,500	1,068	29,556	9,698	562,751	3,027,000	561,683	0.0000
lc_l	196,500	26,313	34,310	9,698	1,651,000	6,200,000	1,624,687	0.0000
lc_obs	196,500	7,045	23,319	9,698	2,776,000	16,270,000	2,768,955	0.0000
catfat_gta	196,500	0.191	0.175	9,698	0.404	0.375	0.213	0.0000
catnonfat_gta	196,500	0.156	0.150	9,698	0.252	0.125	0.096	0.0000
lc_a_gta	196,500	-0.0180	0.139	9,698	0.0440	0.122	0.062	0.0000
lc_l_gta	196,500	0.174	0.0643	9,698	0.208	0.0711	0.034	0.0000
lc_obs_gta	196,500	0.0350	0.0473	9,698	0.152	0.370	0.117	0.0000
Bank-level Variables								
Lerner Index	194,064	0.317	0.107	9,647	0.271	0.134	-0.046	0.0000
Equity Ratio	195,431	0.0947	0.0425	9,666	0.0772	0.0308	-0.018	0.0000
Gross Total Assets	195,433	133,000	144,298	9,667	8,723,000	33,990,000	8,590,000	0.0000
Bank Size	195,633	11.44	0.853	9,682	15.00	1.128	3.560	0.0000
Earnings Volatility	193,388	0.00450	0.00362	9,623	0.00406	0.00313	0.000	0.0000
ZSCORE	184,173	47.83	53.57	9,415	44.70	49.71	-3.130	0.0000
Multi-BHC	196,500	0.236	0.425	9,698	0.614	0.487	0.378	0.0000
Acquisitions	196,500	0.0589	0.235	9,698	0.459	0.498	0.400	0.0000

Table 1: Summary Statistics

Panel C: Summary Statistics (State-level)

	N	Mean	Median	Q1	Q3	SD
State-level Bank Deregulation Variables						
INTRA	1,166	0.894	1	1	1	0.308
INTER	1,166	0.886	1	1	1	0.318
RS Index (4 Restrictions)	1,166	3.032	4	3	4	1.425
KNP Index (5 Restrictions)	1,166	1.467	0	0	2	1.803
KNP Index (4 Restrictions)	1,166	1.774	0	0	3	1.984
State Liquidity Creation Variables						
Liquidity Creation per Capita	1,166	7.465	6.597	4.332	9.399	4.707
Small Bank Liquidity Creation per Capita	1,164	1.414	1.051	0.634	1.917	1.132
Medium Bank Liquidity Creation per Capita	1,106	0.742	0.573	0.332	0.928	0.666
Large Bank Liquidity Creation per Capita	1,047	5.958	4.827	2.877	7.722	4.833
Small/Medium Bank Liquidity Creation per Capita	1,165	2.116	1.665	1.082	2.745	1.500
Asset-side Liquidity Creation per Capita	1,166	0.762	0.595	-0.181	1.624	1.316
Liability-side Liquidity Creation per Capita	1,166	3.660	3.525	2.969	4.178	1.181
Off-balance sheet Liquidity Creation per Capita	1,166	3.042	2.191	1.243	3.719	3.437
State-level Variables						
State-level Deposit per Capita	1,117	8.489	7.962	6.506	10.20	2.925
State-level Equity per Capita	1,117	1.294	1.180	0.933	1.558	0.556
GDP per Capita	1,166	28,053	25,657	19,280	34,035	13,470
Personal Income per Capita	1,166	23.12	22.00	16.54	28.58	8.181
LN(Population)	1,166	15.04	15.13	14.31	15.64	0.995
HPI	1,166	205.5	186.9	135.3	241.6	94.82

Table 2: Relationship between Bank Competition and Bank Liquidity Creation

This table contains OLS panel regressions that examine the relation between bank competition and bank liquidity creation. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1 and 3 include bank and year fixed effects. The specifications in Columns 2 and 4 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

VARIABLES	(1)	(2)	(3)	(4)
Lerner Index	0.0731**	0.0581**	0.142**	0.126**
	(0.0325)	(0.0251)	(0.0680)	(0.0544)
EQRAT			-0.902***	-0.971***
			(0.0946)	(0.0875)
EARNVOL			-0.812	-0.684
			(0.527)	(0.577)
ZSCORE			-5.48e-06	-2.37e-05***
			(7.05e-06)	(6.01e-06)
MBHC			0.0228***	0.0180***
			(0.00220)	(0.00219)
Acquisition			0.00554***	0.00764***
			(0.00184)	(0.00172)
Constant	0.109***	-0.166***	-0.0614	0.167***
	(0.00817)	(0.0375)	(0.240)	(0.0449)
Observations	203,711	203,711	181,141	181,141
Adjusted R-squared	0.777	0.796	0.801	0.814
Control Variables	No	No	Yes	Yes
Macroeconomic Variables	No	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State time trend	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Relationship between Bank Competition and Bank Liquidity Creation: Sub-sample analysis by bank size

This table contains OLS panel regressions that examine the relation between bank competition and bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1, 3, and 5 include bank and year fixed effects. The specifications in Columns 2, 4, and 6 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Small Bank	Small Bank	Medium Bank	Medium Bank	Large Bank	Large Bank
Lerner Index	0.0748***	0.0717***	0.0934	0.0746	0.268	0.195
	(0.0189)	(0.0190)	(0.105)	(0.0731)	(0.391)	(0.395)
EQRAT	-0.893***	-0.957***	-0.167	-0.633	1.428	1.733
	(0.0458)	(0.0456)	(0.453)	(0.419)	(1.440)	(1.702)
EARNVOL	-0.0167	0.221	-2.357	1.489	-25.77*	-26.06*
	(0.188)	(0.187)	(2.208)	(1.491)	(14.51)	(14.29)
ZSCORE	-1.56e-06	-2.07e-05***	1.27e-05	3.01e-05	2.31e-05	-3.44e-05
	(5.70e-06)	(5.51e-06)	(3.06e-05)	(3.63e-05)	(0.000102)	(0.000105)
MBHC	0.0254***	0.0212***	0.00485	-0.00771	-0.0179	-0.0273
	(0.00203)	(0.00199)	(0.00928)	(0.0103)	(0.0177)	(0.0292)
Acquisition	0.00640***	0.00817***	-0.000464	0.00994*	-0.00237	-0.000531
	(0.00172)	(0.00167)	(0.00486)	(0.00587)	(0.0101)	(0.0120)
Constant	0.0749	0.401***	-4.760	0.355***	0.972	0.391***
	(0.253)	(0.0153)	(3.907)	(0.0313)	(1.769)	(0.109)
Observations	171,097	171,097	5,787	5,787	4,257	4,257
Adjusted R-squared	0.801	0.813	0.678	0.774	0.826	0.836
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Variables	Yes	No	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
State time trend	No	Yes	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Relationship between Bank Competition and Bank Liquidity Creation: Sub-sample analysis by liquidity creation components

This table contains OLS panel regressions that examine the relation between bank competition and components of bank liquidity creation. The analysis is at bank-year level. The dependent variable in Columns 1 – 4 is asset-side liquidity creation normalized by GTA. The dependent variable in Columns 5 – 8 is liability-side liquidity creation normalized by GTA. The dependent variable in Columns 9 – 12 is off-the-balance sheet-side liquidity creation normalized by GTA. The independent variable is Lerner Index, which is the observed price-cost margin divided by price. The specifications in Column 1, 3, 5, 7, 9, and 11 include bank and year fixed effects. The specifications in Columns 2, 4, 6, 8, 10, and 12 include bank and state-year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at firm level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Asset-side liquidity creation	Asset-side liquidity creation	Asset-side liquidity creation	Asset-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")
Lerner Index	0.0315***	0.0285***	0.0381***	0.0450***	0.000384	0.000347	-0.000164	-0.00503	0.0412	0.0293	0.104	0.0858
	(0.00463)	(0.00425)	(0.0113)	(0.0115)	(0.00212)	(0.00199)	(0.00524)	(0.00364)	(0.0351)	(0.0264)	(0.0793)	(0.0631)
EQRAT			-0.277***	-0.355***			-0.535***	-0.512***			-0.0905	-0.104
			(0.0392)	(0.0392)			(0.0147)	(0.0137)			(0.0991)	(0.0899)
EARNVOL			0.0306	0.222			-0.104	-0.0286			-0.739	-0.878
			(0.156)	(0.150)			(0.0785)	(0.0757)			(0.519)	(0.575)
ZSCORE			2.46e-06	-1.58e-05***			6.07e-06***	4.81e-06**			-1.40e-05***	-1.27e-05***
			(4.94e-06)	(4.72e-06)			(2.04e-06)	(1.96e-06)			(5.03e-06)	(3.29e-06)
MBHC			0.0218***	0.0173***			-0.00182***	-0.00112*			0.00277**	0.00186
			(0.00172)	(0.00166)			(0.000668)	(0.000647)			(0.00125)	(0.00133)
Acquisition			0.00475***	0.00694***			-0.00269***	-0.00262***			0.00348***	0.00331***
			(0.00126)	(0.00118)			(0.000509)	(0.000495)			(0.00126)	(0.00115)
Constant	-0.0574***	-0.473***	-0.0991	-0.0822**	0.163***	0.217***	-0.0852	0.197***	0.00360	0.0896***	0.123	0.0526***
	(0.00152)	(0.0325)	(0.209)	(0.0356)	(0.000661)	(0.0108)	(0.0650)	(0.0139)	(0.00874)	(0.0146)	(0.0936)	(0.0202)
Observations	203,711	203,711	181,141	181,141	203,711	203,711	181,141	181,141	203,711	203,711	181,141	181,141
Adjusted R-squared	0.741	0.767	0.759	0.778	0.772	0.792	0.801	0.815	0.715	0.750	0.754	0.774
Control Variables	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Macroeconomic Variables	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State time trend	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects of Bank Deregulation on Bank Liquidity Creation

This table presents the estimation results that analyze the effect bank competition on bank liquidity creation. The analysis is at bank-year level. The dependent variable in Column 1 is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The dependent variables in Columns 2, 3, and 4 are asset-side liquidity creation normalized by GTA, liability-side liquidity creation normalized by GTA, and off-the-balance sheet-side liquidity creation normalized by GTA, respectively. The independent variables are INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for Bank Size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Liquidity creation (catfat)	Liquidity creation (catfat)	Liquidity creation (catfat)	Asset-side liquidity creation	Asset-side liquidity creation	Asset-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Liability-side liquidity creation	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")	Off-balance sheet liquidity creation ("fat")
INTRA	0.00301		0.00283	0.00009		-0.00003	0.00482**		0.00482**	-0.00191		-0.00196
	(0.00595)		(0.00596)	(0.00587)		(0.00592)	(0.00202)		(0.00201)	(0.00185)		(0.00184)
INTER		0.0135	0.0135		0.00939	0.00939		0.000365	0.000277		0.00375	0.00379
		(0.00872)	(0.00875)		(0.00997)	(0.00998)		(0.00271)	(0.00262)		(0.00227)	(0.00226)
EQRAT	-0.611***	-0.611***	-0.610***	-0.137**	-0.137**	-0.137**	-0.473***	-0.476***	-0.473***	-0.000202	0.00117	7.94e-05
	(0.0677)	(0.0682)	(0.0679)	(0.0534)	(0.0544)	(0.0536)	(0.0137)	(0.0133)	(0.0137)	(0.0359)	(0.0362)	(0.0360)
Bank Size	0.0193***	0.0195***	0.0196***	0.0240***	0.0242***	0.0242***	-0.018***	-0.018***	-0.018***	0.0130***	0.0132***	0.0131***
	(0.00584)	(0.00592)	(0.00576)	(0.00425)	(0.00424)	(0.00414)	(0.00151)	(0.00153)	(0.00150)	(0.00264)	(0.00276)	(0.00269)
EARNVOL	-0.978	-0.956	-0.956	0.0511	0.0665	0.0665	-0.228**	-0.227**	-0.228**	-0.801	-0.795	-0.795
	(0.827)	(0.822)	(0.821)	(0.231)	(0.228)	(0.228)	(0.0989)	(0.1000)	(0.0977)	(0.783)	(0.779)	(0.779)
ZSCORE	0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000**	0.0000**	0.0000**	-0.0000**	-0.0000**	-0.0000**
	(9.22e-06)	(8.45e-06)	(8.56e-06)	(7.82e-06)	(6.86e-06)	(6.99e-06)	(2.29e-06)	(2.19e-06)	(2.13e-06)	(4.33e-06)	(4.57e-06)	(4.49e-06)
MBHC	0.0218***	0.0217***	0.0216***	0.0191***	0.0189***	0.0189***	-0.0014	-0.0013	-0.0014	0.0042***	0.0041***	0.0041***
	(0.00311)	(0.00316)	(0.00307)	(0.00232)	(0.00234)	(0.00233)	(0.00119)	(0.00121)	(0.00118)	(0.00119)	(0.00122)	(0.00119)
Acquisition	-0.00151	-0.00176	-0.00180	-0.00343	-0.00363	-0.00363	0.0025***	0.0026***	0.0025***	-0.000594	-0.000707	-0.000675
	(0.00289)	(0.00290)	(0.00288)	(0.00255)	(0.00252)	(0.00250)	(0.000883)	(0.000889)	(0.000870)	(0.00103)	(0.00105)	(0.00103)
Constant	-0.0124	-0.0701	-0.0828	-0.154	-0.203	-0.203	0.0778	0.0980	0.0764	0.0634	0.0347	0.0435
	(0.446)	(0.416)	(0.426)	(0.457)	(0.430)	(0.433)	(0.174)	(0.172)	(0.171)	(0.141)	(0.133)	(0.136)
Observations	193,032	193,032	193,032	193,032	193,032	193,032	193,032	193,032	193,032	193,032	193,032	193,032
Adjusted R-squared	0.792	0.793	0.793	0.752	0.752	0.752	0.804	0.803	0.804	0.740	0.740	0.740
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects of Bank Deregulation on Bank Liquidity Creation: Sub-sample analysis by bank size

This table presents the estimation results that analyze the effect bank competition on bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variables are INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for Bank Size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) Small Bank	(2) Medium Bank	(3) Large Bank	(4) Small Bank	(5) Medium Bank	(6) Large Bank
INTRA	0.00359	-0.0289	-0.0391	-0.0195	0.00321	0.00322
	(0.00571)	(0.0237)	(0.0284)	(0.0159)	(0.00590)	(0.00589)
INTER	0.0114	0.0380*	0.0670*	0.0615**	0.0126	0.0130
	(0.00884)	(0.0225)	(0.0346)	(0.0303)	(0.00867)	(0.00877)
Small Bank				0.0393*		
				(0.0213)		
Small Bank * INTRA				0.0231		
				(0.0152)		
Small Bank * INTER				-0.0495*		
				(0.0288)		
Medium Bank					-0.0425	
					(0.0269)	
Medium Bank * INTRA					-0.0142	
					(0.0180)	
Medium Bank * INTER					0.0506*	
					(0.0300)	
Large Bank						-0.0155
						(0.0192)
Large Bank * INTRA						-0.0359**
						(0.0157)
Large Bank * INTER						0.0432
						(0.0297)
Constant	-0.00417	-3.614	1.575	-0.175	-0.136	-0.136
	(0.445)	(3.691)	(2.049)	(0.438)	(0.438)	(0.436)
Observations	183,627	5,372	4,033	193,032	193,032	193,032
Adjusted R-squared	0.793	0.684	0.830	0.793	0.793	0.793
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of Interstate Branching Deregulation on Bank Liquidity Creation

This table presents the estimation results that analyze the effect interstate bank branching deregulation on bank liquidity creation. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variables are RS Index, which ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state, KNP4 Index, which ranges from one (highly regulated) to four (deregulated), KNP5 Index, which ranges from one (highly regulated) to five (deregulated), INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for Bank Size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
RS Index	0.00455**	0.00388*				
	(0.00206)	(0.00229)				
KNP4 Index			-0.00451**	-0.00366*		
			(0.00177)	(0.00196)		
KNP5 Index					-0.00415**	-0.00376**
					(0.00182)	(0.00173)
INTRA		0.000685		0.000722		0.000992
		(0.00602)		(0.00604)		(0.00598)
INTER		0.0116		0.0118		0.0121
		(0.00793)		(0.00803)		(0.00819)
EQRAT		-0.608***		-0.608***		-0.608***
		(0.0676)		(0.0677)		(0.0676)
Bank Size		0.0198***		0.0198***		0.0198***
		(0.00569)		(0.00570)		(0.00571)
EARNVOL		-0.940		-0.940		-0.935
		(0.821)		(0.821)		(0.820)
ZSCORE		-2.87e-06		-2.82e-06		-2.71e-06
		(8.39e-06)		(8.37e-06)		(8.35e-06)
MBHC		0.0214***		0.0214***		0.0214***
		(0.00310)		(0.00310)		(0.00307)
Acquisition		-0.00164		-0.00165		-0.00167
		(0.00289)		(0.00289)		(0.00288)
Constant	0.108***	-0.119	0.126***	-0.104	0.126***	-0.0960
	(0.0148)	(0.417)	(0.00980)	(0.417)	(0.00989)	(0.420)
Observations	206,198	193,032	206,198	193,032	206,198	193,032
Adjusted R-squared	0.773	0.793	0.773	0.793	0.773	0.793
Control Variables	No	Yes	No	Yes	No	Yes
Macroeconomic Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Effects of Interstate Branching Deregulation on Bank Liquidity Creation: Sub-sample analysis by bank size

This table presents the estimation results that analyze the effect interstate bank branching deregulation on bank liquidity creation in small, medium, and large banks. A bank is classified as a large bank if its GTA are exceeding $3 billion, as a medium bank if its GTA are between $1 billion and $3 billion, and as a small bank if its GTA are below $1 billion. The analysis is at bank-year level. The dependent variable is catfat, which is a category-based liquidity creation measure, including both on-balance sheet and off-balance sheet activities, normalized by GTA. The independent variables are RS Index, which ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state, KNP4 Index, which ranges from one (highly regulated) to four (deregulated), KNP5 Index, which ranges from one (highly regulated) to five (deregulated), INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include bank and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level. Different from the previous specifications using Lerner Index as a proxy for bank competition, all specifications in this table control for Bank Size and cluster by state-level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All independent variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Small Bank	Medium Bank	Large Bank	Small Bank	Medium Bank	Large Bank
RSI	0.00288	0.00393	0.0158	0.00886***	0.00374	0.00355
	(0.00223)	(0.00449)	(0.0109)	(0.00294)	(0.00228)	(0.00231)
INTRA	0.00203	-0.0297	-0.0463	0.000594	0.000681	0.000630
	(0.00566)	(0.0237)	(0.0311)	(0.00599)	(0.00599)	(0.00597)
INTER	0.0101	0.0376	0.0640*	0.0117	0.0116	0.0117
	(0.00807)	(0.0225)	(0.0342)	(0.00792)	(0.00793)	(0.00793)
Small Bank				0.0271***		
				(0.00909)		
Small Bank X RS Index				-0.00546**		
				(0.00253)		
Medium Bank					-0.0154	
					(0.0100)	
Medium Bank X RS Index					0.00267	
					(0.00307)	
Large Bank						-0.0303
						(0.0220)
Large Bank X RS Index						0.00871*
						(0.00438)
Constant	0.00672	-3.452	1.709	-0.141	-0.120	-0.107
	(0.431)	(3.612)	(2.067)	(0.420)	(0.417)	(0.419)
Observations	183,627	5,372	4,033	193,032	193,032	193,032
Adjusted R-squared	0.793	0.684	0.830	0.793	0.793	0.793
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year	Bank, Year

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Effects of Bank Deregulation on State-Level Bank Liquidity Creation

This table presents the estimation results that analyze the effect intra- and interstate bank deregulation on state-level bank liquidity creation. The analysis is at state-year level. The dependent variable is state-level aggregate catfat normalized by state population. The independent variables are INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include state and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) State catfat per capita	(2) State catfat per capita	(3) State catfat per capita	(4) State catfat per capita	(5) State catfat per capita	(6) State catfat per capita
INTRA	-1.706**		-1.530**	-0.671		-0.688
	(0.717)		(0.626)	(0.484)		(0.471)
INTER		-1.189	-0.802		-0.0224	0.0997
		(0.847)	(0.744)		(0.522)	(0.496)
LN(Population)				8.686***	8.905***	8.739***
				(3.010)	(2.979)	(3.006)
HPI				-0.0186***	-0.0186***	-0.0187***
				(0.00615)	(0.00617)	(0.00615)
Number of Borrowers				0.00348	0.00396	0.00349
				(0.00334)	(0.00339)	(0.00338)
Number of Competitors				0.00293	0.00358*	0.00294
				(0.00223)	(0.00206)	(0.00224)
Deposit per capita				0.0859	0.0831	0.0866
				(0.185)	(0.188)	(0.187)
Equity per capita				2.822***	2.839***	2.821***
				(0.806)	(0.813)	(0.810)
GDP per capita				0.000268***	0.000266***	0.000268***
				(4.42e-05)	(4.48e-05)	(4.43e-05)
Personal Income per capita				-0.0467	-0.0282	-0.0433
				(0.130)	(0.136)	(0.132)
Constant	0.766**	0.194	0.818**	-132.5***	-136.6***	-133.4***
	(0.312)	(0.311)	(0.318)	(45.14)	(44.63)	(45.19)
Observations	1,176	1,176	1,176	1,127	1,127	1,127
Adjusted R-squared	0.739	0.736	0.739	0.826	0.826	0.826
Control Variables	No	No	No	Yes	Yes	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Effects of Bank Deregulation on State-Level Bank Liquidity Creation by Small and Large Banks

This table presents the estimation results that analyze the effect intra- and interstate bank deregulation on state-level bank liquidity creation. The analysis is at state-year level. The dependent variable is state-level aggregate catfat, created by either small banks within a state or large banks within a state, normalized by state population. The dependent variable in Columns 1 – 6 is state-level small bank catfat normalized by state population, and the dependent variable in Columns 7 – 12 is state-level large bank catfat normalized by state population. The independent variables are INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include state and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) State catfat per capita (Small Bank)	(2) State catfat per capita (Small Bank)	(3) State catfat per capita (Small Bank)	(4) State catfat per capita (Medium Bank)	(5) State catfat per capita (Medium Bank)	(6) State catfat per capita (Medium Bank)	(7) State catfat per capita (Large Bank)	(8) State catfat per capita (Large Bank)	(9) State catfat per capita (Large Bank)
INTRA	0.2870		0.2261	0.4340***		0.3421***	-0.2875		-0.3368
	(0.1882)		(0.1882)	(0.1360)		(0.1177)	(0.3884)		(0.3777)
INTER		0.4032*	0.3635		0.6089***	0.5488***		0.2351	0.2942
		(0.2187)	(0.2199)		(0.1786)	(0.1722)		(0.4555)	(0.4414)
LN(Population)	-0.5245	-0.3884	-0.3347	0.8410	1.0465	1.1277	8.6299***	8.8636***	8.7836***
	(0.9057)	(0.8074)	(0.8202)	(1.0535)	(0.9840)	(0.9777)	(3.2126)	(3.2035)	(3.2223)
HPI	-0.0034*	-0.0036**	-0.0036**	0.0003	0.0001	0.0000	-0.0151**	-0.0153**	-0.0153**
	(0.0017)	(0.0017)	(0.0017)	(0.0011)	(0.0011)	(0.0011)	(0.0060)	(0.0060)	(0.0060)
Number of Borrowers	0.0001	-0.0000	0.0001	0.0003	0.0002	0.0004	-0.0052*	-0.0049*	-0.0051*
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0005)	(0.0029)	(0.0029)	(0.0029)
Number of Competitors	0.0009**	0.0007	0.0009**	-0.0005	-0.0008	-0.0004	0.0018	0.0021*	0.0018
	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0007)	(0.0006)	(0.0012)	(0.0012)	(0.0012)
Deposit per capita	0.1240***	0.1281***	0.1268***	0.0673**	0.0736**	0.0716**	0.3551***	0.3554***	0.3574***
	(0.0231)	(0.0241)	(0.0241)	(0.0317)	(0.0326)	(0.0319)	(0.1133)	(0.1151)	(0.1146)
Equity per capita	-0.2843**	-0.2967**	-0.2850**	-0.0887	-0.1076	-0.0898	0.4821	0.4990	0.4815
	(0.1220)	(0.1256)	(0.1237)	(0.0952)	(0.1004)	(0.0979)	(0.6405)	(0.6432)	(0.6434)
GDP per capita	0.0000	0.0000	0.0000	-0.0000**	-0.0000**	-0.0000**	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Personal Income per capita	-0.0470	-0.0395	-0.0345	-0.0096	0.0016	0.0091	-0.1771	-0.1597	-0.1670
	(0.0624)	(0.0637)	(0.0643)	(0.0512)	(0.0510)	(0.0518)	(0.1366)	(0.1397)	(0.1371)
Constant	8.6803	6.5932	5.5638	-12.0058	-15.1546	-16.7116	-129.9183***	-133.9739***	-132.4408***
	(13.6808)	(12.1136)	(12.3849)	(15.8832)	(14.7960)	(14.7630)	(48.2185)	(48.0960)	(48.4746)
Observations	1,127	1,127	1,127	1,127	1,127	1,127	1,127	1,127	1,127
Adjusted R-squared	0.767	0.770	0.771	0.332	0.344	0.352	0.782	0.782	0.782
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Effects of Bank Branching Deregulation on State-Level Bank Liquidity Creation

This table presents the estimation results that analyze the effect interstate bank branching deregulation on state-level bank liquidity creation. The analysis is at state-year level. The dependent variable is state-level aggregate catfat normalized by state population. The independent variables are RS Index, which ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state, KNP4 Index, which ranges from one (highly regulated) to four (deregulated), KNP5 Index, which ranges from one (highly regulated) to five (deregulated), INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include state and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) State catfat per capita	(2) State catfat per capita	(3) State catfat per capita	(4) State catfat per capita	(5) State catfat per capita	(6) State catfat per capita
RS Index	0.2030	0.0641				
	(0.1847)	(0.1652)				
KNP4 Index			-0.1897	-0.0624		
			(0.1680)	(0.1441)		
KNP5 Index					-0.1984	-0.1130
					(0.1760)	(0.1515)
INTRA		0.1765		0.1762		0.1506
		(0.5047)		(0.4966)		(0.4911)
INTER		1.1687*		1.1689*		1.1556*
		(0.6793)		(0.6803)		(0.6623)
LN(Population)		9.4109**		9.4144**		9.3219**
		(4.4929)		(4.4644)		(4.5044)
HPI		-0.0189***		-0.0189***		-0.0189***
		(0.0060)		(0.0060)		(0.0061)
Number of Borrowers		-0.0046		-0.0046		-0.0046
		(0.0029)		(0.0029)		(0.0029)
Number of Competitors		0.0022		0.0022		0.0022
		(0.0016)		(0.0016)		(0.0016)
Deposit per capita		0.5507***		0.5507***		0.5473***
		(0.1237)		(0.1232)		(0.1222)
Equity per capita		0.1316		0.1319		0.1504
		(0.7125)		(0.7096)		(0.7128)
GDP per capita		0.0002***		0.0002***		0.0002***
		(0.0000)		(0.0000)		(0.0000)
Personal Income per capita		-0.1860		-0.1862		-0.1829
		(0.1291)		(0.1281)		(0.1279)
Constant	3.4432***	-141.3582**	4.2552***	-141.1510**	4.2552***	-139.7925**
	(0.8450)	(67.3184)	(0.2783)	(67.0455)	(0.2781)	(67.6398)
Observations	1,176	1,127	1,176	1,127	1,176	1,127
Adjusted R-squared	0.707	0.760	0.707	0.760	0.707	0.760
Control Variables	No	Yes	No	Yes	No	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Effects of Bank Branching Deregulation on State-Level Bank Liquidity Creation by Small and Large Banks

This table presents the estimation results that analyze the effect interstate bank branching deregulation on state-level bank liquidity creation. The analysis is at state-year level. The dependent variable is state-level aggregate catfat, created by either small banks within a state or large banks within a state, normalized by state population. The dependent variable in Columns 1 – 6 is state-level small bank catfat normalized by state population, and the dependent variable in Columns 7 – 12 is state-level large bank catfat normalized by state population. The independent variables are RS Index, which ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state, KNP4 Index, which ranges from one (highly regulated) to four (deregulated), KNP5 Index, which ranges from one (highly regulated) to five (deregulated), INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. All specifications include state and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) State catfat per capita (Small Bank)	(2) State catfat per capita (Small Bank)	(3) State catfat per capita (Small Bank)	(4) State catfat per capita (Medium Bank)	(5) State catfat per capita (Medium Bank)	(6) State catfat per capita (Medium Bank)	(7) State catfat per capita (Large Bank)	(8) State catfat per capita (Large Bank)	(9) State catfat per capita (Large Bank)
RS Index	0.1718***			0.1039**			-0.2116		
	(0.0459)			(0.0409)			(0.1692)		
KNP4 Index		-0.1479***			-0.0912**			0.1766	
		(0.0405)			(0.0368)			(0.1445)	
KNP5 Index			-0.1387***			-0.0926**			0.1183
			(0.0379)			(0.0410)			(0.1411)
INTRA	0.0791	0.0953	0.1270	0.2531*	0.2614**	0.2759**	-0.1556	-0.1805	-0.2523
	(0.1647)	(0.1671)	(0.1744)	(0.1306)	(0.1298)	(0.1288)	(0.4198)	(0.4112)	(0.3982)
INTER	0.2619	0.2743	0.3010	0.4874***	0.4939***	0.5071***	0.4194	0.4007	0.3475
	(0.2031)	(0.2049)	(0.1990)	(0.1642)	(0.1664)	(0.1600)	(0.4528)	(0.4520)	(0.4498)
Constant	11.5443	11.3385	10.2212	-13.0933	-13.1511	-13.6015	-139.8093***	-139.3385***	-136.4121***
	(11.8569)	(11.9013)	(12.3682)	(15.0485)	(15.0025)	(15.3552)	(48.6442)	(48.4717)	(48.4128)
Observations	1,127	1,127	1,127	1,127	1,127	1,127	1,127	1,127	1,127
Adjusted R-squared	0.786	0.784	0.781	0.363	0.361	0.361	0.783	0.783	0.782
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Effects of Bank Deregulation on Local Loan Creation

This table presents the estimation results that analyze the effect of bank deregulation events on state-level loan creation. Panel A shows the results that examine the effect of intra- and interstate bank deregulation on state-level loan creation, and Panel B shows the results that examine the effect of interstate bank branching deregulation on state-level loan creation. The analysis is at state-year level. Because of significant missing observations before 1987, the sample period for the analysis in this table is from 1987 – 2007. The dependent variable is state-level aggregate loan creation measures. The dependent variables are natural log of state-level loan creation in Columns 1 and 5, state-level loan creation normalized by state population in Columns 2 and 6, state-level loan creation normalized by number of borrowers within a state in Columns 3 and 7, and state-level loan creation normalized by number of competitors within a state in Columns 4 and 8, respectively. The independent variables are RS Index, which ranges from zero (deregulated) to four (highly regulated) based on regulation changes in a state, KNP4 Index, which ranges from one (highly regulated) to four (deregulated), KNP5 Index, which ranges from one (highly regulated) to five (deregulated), INTRA, which is equal to 1 from the year of intrastate deregulation onward and 0 prior to the deregulation, and INTER, which is equal to 1 from the year of interstate deregulation onward and 0 prior to the deregulation. Control variables include ln(Population), HPI, Number of Borrowers, Number of Competitors, State Deposit per capita, State Equity per capita, and GDP per capita, and Personal Income per capita. All specifications include state and year fixed effects. Standard errors are adjusted for potential heteroskedasticity and for group correlation at state level to allow for an arbitrary serial correlation within state over time because the deregulation variables vary at the state level. All control variables are lagged. Robust standard errors in parentheses. Asterisks indicate significance at 0.01 (***), 0.05 (**), and 0.10 (*) levels.

	(1) ln(Loan Creation)	(2) ln(State Loan per capita)	(3) ln(State Loan per borrowers)	(4) ln(State Loan per competitors)	(5) ln(Loan Creation)	(6) ln(State Loan per capita)	(7) ln(State Loan per borrowers)	(8) ln(State Loan per competitors)
RSI					0.0110	0.0113	0.0053	0.0093
					(0.0300)	(0.0300)	(0.0314)	(0.0338)
INTRA	0.1577	0.1541	0.2385	0.1928	0.1459	0.1420	0.2329	0.1828
	(0.1999)	(0.1998)	(0.1896)	(0.2113)	(0.1935)	(0.1934)	(0.1862)	(0.2040)
INTER	0.2061	0.2050	0.1376	0.1923	0.1975	0.1962	0.1335	0.1850
	(0.4047)	(0.4040)	(0.4075)	(0.3990)	(0.4109)	(0.4103)	(0.4126)	(0.4073)
Constant	14.3260	14.0380	15.8956	30.2601***	14.7622	14.4828	16.1036	30.6282***
	(11.1364)	(11.1561)	(9.9597)	(9.9420)	(11.2671)	(11.2921)	(10.1552)	(10.0347)
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Adjusted R-squared	0.876	0.747	0.674	0.852	0.876	0.747	0.674	0.851
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year	State, Year

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Credit Access and Household Well-being: Evidence from Payday Lending*

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Jaeyoon Lee †

October 9, 2017

Abstract

How does gaining access to expensive credit affect the well-being of credit-constrained households? I use plausibly exogenous zip code-level variation in the temporal accessibility of payday loans to examine the causal effects of access to payday loans on household well-being. Using suicide attempts and deaths as a measure for household distress, I find detrimental effects from payday loans; that is, having access to payday loans substantially increases suicide risk. The dynamic analyses show that there is no existing trend during the pre-payday periods; however, a sharp increase in attempted suicides emerges only after gaining access to payday loans. Further analyses show that the effects are significant only among people who are effectively eligible for payday loans—the employed and those with private insurance—especially in zip codes with a high share of finance-constrained households. Finally, increased suicide risk in zip codes with access to payday loans appears to be related to mental health deterioration from financial distress.

JEL Codes: D14, D18, G23, G28, I31

Keywords: Credit Access, Payday Loan, Household Finance, Well-being, Suicide Risk

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1 Introduction

Does expanding access to expensive credit improve the well-being of borrowers? Traditional economic theories suggest that credit allows households to smooth consumption over their life cycles and to invest in both physical capital and human capital. In this view, high-cost credit, such as payday loans, should not cause social welfare losses as long as the market is highly competitive and borrowers and lenders understand the risks and costs involved in the transactions. Thus, a high interest rate is just a trade-off between present consumption over future consumption. In recent decades, traditional models with symmetric information and rational, time-consistent borrowers have been challenged by a radically different alternative called behavioral economics. This view offers extensive examples of consumers' divergence from rationality owing to behavioral bias, for example, self-control problems, time-inconsistent preferences, over-optimism, over-confidence, narrow framing, and present bias.[1]

Similarly to the ambiguous predictions from economic theories, empirical evidence is mixed on the effects on consumer welfare of having access to high-cost credit. With respect to payday loans, a strand of research finds evidence for positive effects of credit supply on household well-being (Zaki, 2016; Parsons and Van Wesep, 2013; Morse, 2011; Morgan et al., 2012; Morgan and Strain, 2008). On the other hand, other studies report negative effects (Zinman, 2010; Agarwal et al., 2009; Carrell and Zinman, 2014; Skiba and Tobacman, 2009; Morgan et al., 2012; Melzer, 2011), while yet others find null effects (Bhutta, 2014; Bhutta et al., 2015).

Overall, there is a lack of consensus in both theoretical and empirical research on whether expanded credit to financially constrained households does more good than harm, especially when expensive credit, such as payday loans, is at the center of the discussion. The main goal of this study is to empirically test whether access to expensive loans benefits or harms

[1]See Zinman (2014) for a review of theoretical work on household debt.

borrowers, with a particular interest in the measure for the longer-term well-being of borrowers, which has not been examined in the literature. Such an analysis that aims to establish a causal link from credit supply, or access to credit, to borrowers' well-being faces several challenges. This is because omitted factors could potentially affect both access to credit and well-being of borrowers. One such challenge is location choices by payday lenders. Payday lenders choose to enter a geographical market where high demand for such short-term loans is present or expected, that is, locations where a large proportion of households are credit-constrained and demand for credit is not satisfied by mainstream financial institutions. Examples of such locations include military bases (Carrell and Zinman, 2014; Carter and Skimmyhorn, 2016; Flannery and Samolyk, 2005) and areas with a large share of low- to moderate-income households (Melzer, 2011) and minority groups (King et al., 2005).

The second challenge is regulations on financial institutions. A state's regulatory forces might endogenously react in multiple ways to the state's economic conditions and the availability and scope of the local social welfare system. In addition, lobbying efforts by alternative financial services providers, such as payday lenders, are an endogenous factor. Lobbying incentives by payday lenders are based on the profitability of and demand for payday loans, and lobbyists have the ability to influence payday-related bills in state legislatures.[2] These factors tend to have disproportional impacts on financially constrained populations who are likely to have high demand for emergency loans. If any of the omitted variables are at play—that is, the availability of payday loans is correlated with unobserved regional factors that potentially affect the well-being of borrowers—then the estimates of our models will be biased.

To address the endogeneity concerns of credit access, I use an identification strategy that isolates the variation in access to credit from potentially endogenous state and local economic conditions. This strategy, similar to that in Melzer (2011), uses the proximity of zip codes in

[2]Not surprisingly, Fox and Mierzwinski (2000) find intense lobbying activities by lobbyists hired by payday lenders in the late 1990s and report that lobbying strategy seems to be working to enact financial services providers' preferred version of legislation.

states that ban payday loans ("payday-banning states" hereafter) to the borders of states that allow payday loans ("payday-allowing states" hereafter). In addition, this strategy compares the changes in household well-being between zip codes with and without close proximity to payday-allowing states, before and after the emergence of payday lending in the neighboring states.[3] The idea behind this identification strategy is quite simple. Residents in zip codes living close to a neighboring payday-allowing state can easily cross the border to take out payday loans because travel costs are low. However, those who live far from the border have little incentive to cross the border to borrow $500 from payday lenders, because the total travel costs increase proportional to the distance and time traveled. Therefore, this strategy mitigates endogeneity issues by focusing on changes in the variation in credit availability of zip codes in states that never allowed payday lending but have a contiguous state with payday stores that have rapidly emerged.

For the measure of borrowers' well-being, I use suicide risk. Both suicide attempts and deaths are extreme cases of household distress. According to a theoretical model in Daly et al. (2013), individuals have different thresholds for suicide, and any negative shocks to happiness (e.g., unemployment and financial difficulties) can cause an individual to locate below his or her life satisfaction threshold for suicide. In addition, Hamermesh and Soss (1974) develop an economic theory of suicide that explains why people commit suicide. According to the model, an individual might end his or her life if the total discounted lifetime utility falls below zero. Suicide risk in this sense is a measure of longer-term changes in well-being (or distress) compared to measures of short- or mid-term changes in well-being, which are used in the existing empirical literature (e.g., bank overdrafts, late bill payments,

[3]While the core idea is similar to that of other studies that use the identification strategy in Melzer (2011), a major improvement of this research's identification strategy is that it uses zip code instead of county as the geographic unit. As explained in a later section, accurately measuring the shortest distance of a zip code to the border of neighboring states that allow payday loans is at the heart of this empirical identification strategy. By using zip codes rather than county codes, which might assign somewhat erroneous distance-to-border measures, I minimize measurement errors in the construction of the essential variable in my empirical models. Moreover, complemented by zip code-level demographic information from the census data (e.g., household incomes, poverty rates, and education levels), my strategy allows for much finer identification of credit-constrained households.

and personal bankruptcies), which evaluate only current or near future utilities. A suicide attempt might be the optimal choice for some people with persistent distress whose stream of future expected utilities is dismal.

The findings of this study favor the view that access to dangerous credit adversely affects consumers' long-term well-being. Gaining access to payday loans substantially increases suicide attempts by 10%. The baseline finding is supported by additional analyses that take advantage of the main eligibility criterion for payday loans—employment of applicants.[4] The effects of access to payday loans on suicide risks are significant only among those aged under 65 years, while the elderly person who is less likely or unlikely to be eligible for payday loans does not experience increased suicide attempts. Moreover, only people with private insurance or the employed increase suicide attempts and I find no significant effects for the uninsured or beneficiaries with Medicare and Medicaid. Further analyses show that zip codes with higher demand for payday loans experience significantly larger increases in attempted suicides. Finally, the results from a diverse set of robustness tests and a placebo test suggest that the relationship between access to payday loans and increased suicide attempts is not coincidental.

Overall, the most conservative estimate, 10%, implies there were an additional 5.5 suicide attempts per 100,000 people, which, if converted to the national level, would amount to an additional 15,000 suicide attempts in 1998. As such, the results suggest there is a large social cost from increased suicide attempts (and suicide deaths) caused by gaining access to payday loans. At a minimum, suicide attempts incur annual medical costs of $142 million in the late 1990s and early 2000s.[5]

How is gaining access to this expensive credit linked to increased suicide risks? First, payday loans cause financial distress for many consumers. It is apparent that a significant

[4]Although unemployed retirees who are mainly on Social Security might still qualify for payday loans, not all payday loan lenders accept applications from such unemployed retirees, possibly because there are no wages to be garnished from them they were to miss payments. With these increased costs and possible stricter screening for retired applicants, there would be much less incentive for the elderly to travel to a payday lender.

[5]In the sample used in this study, the average medical charge per attempted suicide is $9410.

share of payday borrowers becomes trapped in financial distress: 80% of loans are not paid off by the first due date and, as Figure 1 shows, 50% of all loans become part of long sequences of more than 10 loans (CFPB, 2014).[6] Second, excessive debts, in turn, could lead to deterioration in the mental health of borrowers through stress. A growing body of literature suggests that stress is associated with deterioration in both physical and mental health (McEwen, 1998; Cooper, 2004; Schneiderman et al., 2005). If financial distress increases overall stress level, we expect that changes in household balance sheets will affect health and healthcare usage as well. Indeed, studies find support for this link (e.g., Gross and Tobacman (2014); Evans and Moore (2011); Dobkin and Puller (2007); Parker et al. (2013); Currie and Tekin (2015); Deaton (2011)). Thus, if excessive financial debts adversely affect mental or emotional health, payday borrowers can develop suicidal ideation.

This research provides evidence that mental health plays a role in explaining the link between financial distress and increased suicide risk. Payday borrowers who suffer from mental well-being deterioration might consult a doctor in outpatient settings to obtain prescription antidepressants. Emotional and mental instability caused by financial problems can exacerbate borrowers' suicide risks and, as a result, people in such circumstances might choose prescription drugs as a method to commit suicide, as antidepressants are within quick and easy reach before their suicidal impulses diminish. The results from a test for the mental health explanation confirm this hypothesis; suicide attempts by poisoning with antidepressants—drugs used for the treatment of mental instability—significantly increase after gaining access to payday loans. This effect is prominent only for those aged under 65 years, who are the main consumers of payday loans. Although my data do not allow for an examination of the exact responses of the number of antidepressant prescriptions on the intensive margin (existing patients who had been taking antidepressants before obtaining access to payday loans) and the extensive margin (new patients who started to take antide-

[6]The right tail in the distribution of payday loan sequences in Figure 1 is important, especially because borrowers with those loans would have paid more than twice as much fees as the original loan amount. For example, since it costs on average $100 per renewal (rollover) on a $500 loan, 10 or more renewals would amount to $1,000 or more.

pressants owing to payday loans), the stark increase in suicide attempts by poisoning with psychotropic drugs is unlikely to be fully driven by the patients who already had mental distress.[7]

The findings of this study relate to the extensive literature examining the effects of access to payday loans on diverse economic and welfare outcomes. To the best of my knowledge, the use of the measure of long-term well-being—suicide risks—as well as mental health explanation is new to the literature. In addition, using zip-level data in the construction of the distance-to-borders measure, this research reduces measurement errors compared to county- or state-level distance measures used in prior studies.

Furthermore, this study is related to a growing body of work that evaluates how financial and economic conditions are linked to health, especially suicide. Studies identify unemployment and permanent income shocks as the two main economic factors that contribute to the risk of suicide (Henry and Short, 1954; Hamermesh and Soss, 1974; Kposowa, 2001; Mortensen et al., 2000). In addition, the existing literature finds that, unlike mortalities from other causes, suicide is the only exception that is highly counter-cyclical; in other words, only suicide mortalities increase during recessions (Ruhm, 2000; Luo et al., 2011; Gerdtham and Johannesson, 2003; Granados, 2005; Evans and Moore, 2011). The findings of my study complement the previous research, in that I provide evidence for a mental health channel through which financial distress can affect the risks of suicide.

The rest of the paper proceeds as follows. Section 2 provides background on the payday lending industry and briefly reviews theories and the previous empirical literature. Section 3 introduces the data and describes the empirical strategy. Section 4 presents the empirical results. Finally, Section 5 concludes.

[7]To the best of my knowledge, for this research's period of interest, no data are available that contain drug prescription or usage information at the individual level in outpatient and physician's office settings.

2 Institutional Background and Literature Review

2.1 Background on Payday Lending Industry

A payday loan is a short-term, high-interest consumer loan with maturity period of 2 weeks. The common loan amount is less than \$500 with an associated fee of \$20 per \$100 advanced. During the underwriting process, the lender typically verifies the borrower's identification, bank account, record of previous pay stubs, and personal information. If approved by the lender, the borrower writes a post-dated check for the principal amount plus fees. While a payday loan has a fixed 2-week maturity, rollovers are common.[8]

The payday lending industry has been hotly debated since its inception, due to the usurious interest rates charged by lenders and frequent rollovers by borrowers and this controversial industry remains under scrutiny today.[9] Proponents of this high-cost, short-term credit argue that payday loans help desperate borrowers solve temporary cash flow issues by providing easy-to-obtain liquidity, which otherwise would not be accommodated by mainstream lenders. Opponents, however, are concerned that payday loans can be harmful, becoming an endless "debt-trap" owing to high fees and rollover feature.[10]

The payday lending industry emerged in the mid-1990s. A series of banking deregulations in the 1980s and 1990s increased the competitive environment in mainstream banking. Competition incentivized many financial institutions to exit the market for less-profitable short-term loans and instead to focus more on profitable longer-term loans. This gap between demand for and supply of short-term credit has since been filled by alternative financial services providers, such as payday lenders.[11] Before the mid-1990s, there were only a small

[8] Rolling-over a loan is in practice identical to taking out a new loan with an incremented amount. For example, if a borrower takes out a first loan for \$100, she would write a check for \$120, including the fees of \$20. If this loan were to be rolled over, she would then write a new check, with the first check voided, for \$140, which is the original check amount plus additional fees of \$20.

[9] An average payday borrower who renews a loan of \$400 eight times would end up with more finance fees, \$640, than the original loan amount, \$400.

[10] CFPB (2014) finds that the majority of payday loans—four out of five—are rolled over within the 2-week period.

[11] See Caskey (2005) and Barr (2004) for more detailed discussion of the background on the emergence of

number of check cashers, pawn shops, and other alternative financial services providers participating in cashing paychecks, but thereafter, a skyrocketing number of outlets began to engage in payday lending, resulting in explosive growth rates. Exponential growth was observed across the nation (Fox, 1998, 1999; Barr, 2004; Caskey, 2005; Stegman, 2007; Melzer, 2011). For instance, in Indiana, one of the few states that collected state-wide statistics on payday lenders, the number of payday lenders skyrocketed five-fold and the loan volume eight-fold (from $12 million to $98 million) in 2 years (Fox, 1998). Another example is a Tennessee payday loan company, Check Into Cash, which reported a three-fold increase in loan volume in 1996 from the previous year.[12] As a result of the exploding number of payday lenders, payday outlets became more prevalent than even McDonald's and Burger King combined: there were more than 22,000 payday stores in 2004 versus 21,000 combined McDonald's and Burger King branches (Karger, 2005; Barr, 2004).

New York and New Jersey banned payday lending during the entire sample period of this study from 1994 to 2000. As Figure 2 shows, among the neighboring states of New York and New Jersey, only Delaware and Pennsylvania allowed payday lending in this period. In Delaware, licensed non-depository lenders were allowed to lend without any cap on interest rate (5 Del. C. § 2201-2244). According to Delaware's Office of the State Banking Commissioner, the first appearance of payday lending was E Z Cash of Delaware, Inc. in July 1998. Throughout the sample period, Pennsylvania imposed bans on payday lending using a rate ceiling that lenders can charge on a loan (P.A. 7 P.S. § 6201-6219). Lenders in Pennsylvania, however, successfully evaded state small loan and usury laws based on a legislative loophole that permits brokering loans (P.A. 73 P.S. § 2181-2192). In other words, they formed partnerships with chartered financial institutions, which were exempt from usury laws and small loan laws, to offer small loans and claimed themselves to be "brokers" so as to avoid regulatory restrictions. Several reports and previous studies indicate that payday lenders did not

the payday lending industry

[12]See Fox et al. (1997) and Fox (1998) for more examples on how fast the payday lending industry grew after the mid-1990s.

begin their operations in Pennsylvania before 1997 (Fox, 1998; Melzer, 2011; Brickley, 1999). In all other neighboring states to New York or New Jersey (i.e., Connecticut, Massachusetts, and Vermont), payday loans were effectively prohibited for the entire sample period.

The rise of payday lending in Delaware and Pennsylvania provides a good source of temporal and geographic variations in access to payday loans to borrowers who reside in the payday-banning states of New York and New Jersey. Because only those who live close enough to the payday-allowing states gain access to payday loans by crossing the borders, those who live "economically" far from the borders of those states would not gain access. Therefore, this study's identification strategy takes advantage of the natural experiment in the supply of payday loans in order to identify the causal effects of gaining access to short-term, high-interest loans on borrowers' distress.

2.2 Suicide Attempts and Mortalities as Measures of Household Distress

Economists recognize that a subjective well-being measure can be useful in the analysis of consumer preferences and social welfare. However, unlike researchers outside economics, such as psychologists, who have long been undertaking subjective well-being research, economists have begun to undertake empirical research in this area only in recent decades. The main reason for the late development is economists' skepticism about the quality of subjective well-being data. Critics argue that self-reported measures commonly used in the subjective well-being research are not reliable, because respondents of a survey can answer quite differently depending on the wording and order of the survey questions; respondents can have an ambiguous understanding of what happiness and life satisfaction really mean in the questionnaires; and the attitudes of survey participants can be non-coherent (Deaton and Stone, 2013; Kahneman and Krueger, 2006; Daly et al., 2013; Bertrand and Mullainathan, 2001; Wilkinson, 2007; Daly et al., 2011; Krueger and Schkade, 2008).[13]

[13]Among studies that report the divergence between self-reported measures of subjective well-being and revealed preferences, an interesting and relatively recent one is Benjamin et al. (2014). They survey U.S.

To overcome these unreliability concerns of self-reported well-being measures, I use suicide attempts and mortalities as a measure of distress or negative subjective well-being. As Oswald (1997) states, suicide data offer "intrinsically more compelling" information about individuals' responses to unhappiness than survey participants' answers to questionnaires, and cannot be performed in an experiment setting. Thus, suicide risk has been studied in both theoretical and empirical research. According to the theoretical model in Daly et al. (2013), individuals have different thresholds for suicide, and any gradual or abrupt changes in happiness can cause them to locate substantially below their suicide thresholds.[14] In addition, Hamermesh and Soss (1974) develop an economic theory of suicide that explains why people commit suicide. According to the model, an individual takes his or her life if the discounted total lifetime utility falls below zero. With increased risk of suicide, people might commit suicide. A suicide attempt or death by an individual, therefore, is a revealed choice after a thorough examination of the utility of continuing one's life.

Consistent with the theory, empirical research has found considerable association between suicide and subjective well-being, and researchers have used suicide as a reliable measure of well-being. Using cross-country panel data, Helliwell (2007) shows a negative association between subjective well-being and suicide.[15] Stevenson and Wolfers (2006) examine the effects of unilateral divorce law on suicide, as well as other measures of family distress, such as domestic violence and spousal homicide, and conclude that female suicide declined by 8% to 16%. Daly et al. (2011, 2013) use suicide to test whether the relative status of being poorer or less happy relatively to others in a neighborhood affects suicide risk. Instead of relying on unreliable subjective measures, it would be more reliable to use the revealed outcomes to understand the well-being of populations.

medical students who are enrolled in the National Residence Matching Program and find stark differences between actual residents' choices and students' subjective well-being rankings.

[14] Although negative shocks to happiness change only the suicidal outcomes of marginal people who become located below their suicide thresholds, research shows that the general population whose members are well above their suicide thresholds also shifted down in the happiness distribution (Daly and Wilson, 2009).

[15] Case and Deaton (2015) find no association between suicide and life satisfaction. Using the same data, however, I find a negative correlation between them. The difference between their and my analyses come from the inclusion of self-evaluation about one's future life (Lee, 2017).

Moreover, suicide risk is a better measure of the changes in the long-term well-being of a population. The outcome variables employed in the existing literature are mostly measures of temporary or transitory states of well-being; examples include foreclosures (Morse, 2011), bounced checks (Morgan et al., 2012; Morgan and Strain, 2008), bankruptcies (Morgan and Strain, 2008; Skiba and Tobacman, 2009; Morgan et al., 2012), bank overdrafts and late bills (Zinman, 2010; Melzer, 2011), credit card delinquency (Agarwal et al., 2009), and job performance (Carrell and Zinman, 2014). Among them, the most long-term welfare consequence is personal bankruptcy. Even bankruptcy does not have significantly lasting effects on the filers, mainly because its purpose is to provide debt relief, or a fresh start, for those who are in severe financial trouble.[16] Suicide risk, however, is a measure of long-term well-being, because a person has to examine his or her stream of current and future expected utilities before making a suicide decision. Put differently, even though an individual might encounter temporary financial distress, if he or she sees a brighter near future, this person would not develop suicidal ideation. On the other hand, a person could be suicidal if he or she expects a consistent and permanent dismal future.

In addition to the reliability and long-term measure advantage, suicide risk is an important measure of well-being in the field of household finance. First, a suicide decision is closely related to changes in a household's financial circumstances, which are often exacerbated by negative shocks, such as personal emergencies and unemployment. In particular, the suicide literature has identified that unemployment and negative permanent income shocks are the two main economic factors that contribute to the risk of suicide (Henry and Short, 1954; Hamermesh and Soss, 1974; Kposowa, 2001; Mortensen et al., 2000; Evans and Moore, 2012; Ruhm, 2000; Granados, 2005; Gerdtham and Johannesson, 2003; Pierce and Schott, 2015). Moreover, recent empirical studies confirm that, unlike mortalities from other causes that are pro-cyclical, suicide is an exception that is highly counter-cyclical, meaning that there

[16]The bankruptcy record is deleted after 7 or 10 years from the filing date of the bankruptcy, depending on the chapter of bankruptcy. However, the recovery of credit takes a relatively shorter amount of time (Jagtiani and Li, 2015); bankruptcy filers continue to receive credit card solicitations, though with inferior terms and conditions (Han et al., 2015); and the filers continue to work similar hours (Han and Li, 2007).

are more suicide mortalities during recessions (Ruhm, 2000; Luo et al., 2011; Gerdtham and Johannesson, 2003; Granados, 2005). Ruhm (2000) finds that a 1 percentage point increase in the unemployment rate is associated with a 1.3% increase in suicides. The strong association of suicides with business cycles, according to the author's conjecture, is due to deterioration in mental health caused by unemployment. My research provides evidence on the connection between household finance and suicide risk, with a particular focus on the mental health channel.

By using suicide attempts, I examine a causal link between the changes in household balance sheets that are attributable to newly gained access to payday loans and the subjective evaluation of borrowers' well-being measured by suicide outcomes. Of course, there are also non-economic factors that affect the risk of suicide among people; for instance, personal events, such as the passing of family or loved ones and development of mental illness. As long as these non-economic factors are uncorrelated with access to payday loans or with the proximity of these people's locations to borders of payday-allowing states, then my estimates will not be confounded by the non-economic factors.

3 Empirical Analysis

3.1 Suicide Attempts and Deaths data

For the analysis, I use the State Inpatient Databases (SID) for New York and New Jersey for the years 1994–2000, constructed by the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project (HCUP).[17] The HCUP collects the universe of discharge-level inpatient data from states with partnership. Each discharge record includes

[17] As explained earlier, this study focuses on states that never allowed payday lending but have a contiguous state that eventually allow payday lending. New York and New Jersey are the only two states before 2000 that share a border with a payday-allowing state and provide zip code information of inpatients to HCUP. I choose 2000 as the final year of this study's analysis period because of the rapid expansion of the Internet in the early 2000s, which has increased demand for and supply of online payday loans. In general, few state laws prevent individuals from obtaining payday loans that are offered by out-of-state or online lenders. Moreover, the patent of Prozac, the most popular antidepressant, expired in August 2001. To minimize any possible spurious correlations that could bias the results of this research, I choose 1994 to 2000 as the sample period of this project.

demographic information of the discharged patient (e.g., age, sex, and race), diagnostic and procedure codes, admission type, length of stay, total medical charges, payer information, and, most importantly, zip code of the patient. Since one of the main contributions of this study to the literature is the utilization of more detailed geographic units, zip code information is crucial.

Each diagnosis category is constructed according to Clinical Classifications Software (CCS) for the ninth version of International Classification of Disease (ICD-9) (HCUP, 2010). For the list of CCS codes used to construct the outcome variables employed in this study, see the appendix. The dependent variables are the numbers of attempted suicide discharges by a variety of demographic groups, which are aggregated to the zip code level in each year. The data include more than 18 million discharge-level observations over 7 years, 1994–2000. The large sample size is critical because it enables the analysis of research to capture changes in hospitalizations of relatively rare events, attempted suicides. In addition, I supplement the zip code-level hospital data with demographic information from the 1990 decennial census.

One concern about the use of suicide attempt data is that the rates of (failed) suicide attempts are greater than those of (successful) attempts, or suicide deaths.[18] To address this concern, I also use suicide mortality data from the National Center for Health Statistics (NCHS). The NCHS data are a census of death records that list the cause(s) of death for deceased. Due to the confidentiality restrictions of the NCHS, the smallest geographic unit is a county.[19]

3.2 Payday Access Measure

Similarly to Melzer (2011), I consider zip-to-border distance to construct the measure for proximity of a zip code to a border of its neighboring states. In this study, therefore,

[18]Suicide mortality was 6.9 per 100,000 people and attempts were 52.3 per 100,000 people in New York and New Jersey during 1994–2000, which equated to 7.6 attempts per completed suicide. The correlation between suicide attempt and suicide death is 88.2 for the period. Such a high correlation is highly anticipated.

[19]In addition, the confidentiality restrictions require that any mortality counts less than 10 be suppressed. I use the unsuppressed, county-level version of the data, provided by the NCHS. For the publicly available mortality data, see `https://wonder.cdc.gov/mortSQL.html`. Researchers who are interested in using the unsuppressed data can submit an application to the NCHS.

any zip codes in New Jersey and New York that are less than 25 miles from a border of either Pennsylvania or Delaware (the shaded area in Figure 3) are considered to have access to payday loans after payday lending emerged in Pennsylvania and Delaware.[20] All other zip codes in New Jersey and New York are considered to have no access throughout the sample period, 1994–2000.[21] The construction of the payday access variable is based on the assumption that people travel across borders to take out payday loans. As expected, Melzer (2011) and Bhutta (2014) find evidence that there are significantly more payday stores along the borders of payday-banning states.

3.3 Summary Statistics

Table 1 presents summary statistics on demographics, business patterns, and hospitalization rates of zip codes in payday-banning states (New York and New Jersey). The first two columns are summary statistics for zip codes within 25 miles of a border of Pennsylvania or Delaware (labeled *Payday Border*), and the last two columns are for those farther than 25 miles away from the two borders (labeled *non–Payday Border*).

There are slight differences between the two groups of zip codes. The payday border zip codes, on average, have smaller population, fewer number of business establishments, and slightly lower annual payroll. Moreover, the main dependent variable, suicide attempt, is a bit more common in zip codes bordered with a payday-allowing state. Other than these differences, the two zip code groups, stratified by payday access, have similar characteristics.

[20]New Jersey is geographically separated from Delaware by Delaware River that runs through the entire border between New Jersey and Delaware. However, most residents in New Jersey can easily travel to Delaware via 28 bridges. To minimize incorrect assignments of payday access measure, instead of relying on birds-eye-view distances that ignore separations by the river, I manually recoded the travel distances between New Jersey's affected zip codes and Delaware. In fact, some zip codes in Cape May County and Cumberland County at the bottom part of New Jersey required a recoding of the payday access measure. Thus, these zip codes are coded to have no access to payday stores in Delaware (based on the 25 mile cutoff) throughout the sample period.

[21]As in Melzer (2011), the results are not sensitive to the chosen distance, 25 miles. Regression results that use other distances will be provided upon request.

3.4 Estimation Framework

Due to the count nature of inpatient data, I use a fixed-effects Poisson model. Specifically, I estimate the conditional expectation of the outcome measures as

$$\mu_{zct} = \exp\left(\alpha_z + \beta Payday_{zt} + X'_{zt}\delta + Border_z \cdot t + \gamma_t + \eta_c \cdot t + \epsilon_{zt}\right), \tag{1}$$

where μ_{zct} is the expected number of an outcome measure (e.g., the number of attempted suicide discharges and other discharge categories) by residents of zip code z and county c in New York or New Jersey in year t. α_z represents a fixed effect for the zip code that controls for time-invariant differences in observable (e.g., the relative size and characteristics of population of the zip code) and unobservable characteristics. The inclusion of zip code fixed effects leads to the identification of the effects of payday access, β, solely from within the zip code variation across time. $Payday_{zt}$ is a dummy variable that equals one if the zip code in New York or New Jersey is within 25 miles of any Pennsylvania or Delaware border after the rise of payday lending in Pennsylvania or Delaware, and zero otherwise. X_{zt} represents a set of time-varying controls, which includes the logarithms of zip code-level average annual payroll, total number of employees and establishments, and total number of all inpatient discharges. $Border_z \cdot t$ is the linear time trend for bordered areas, where $Border_z$ equals one if the zip code is located within 25 miles of any border and, zero otherwise. This linear time trend for the border captures any secular differences across areas depending on the proximity to a state border. γ_t captures the synthetic year fixed effect. Furthermore, $\eta_c \cdot t$ represents a county-specific linear time trend, and ϵ_{zt} represents an error term.

The identifying variation in the *Payday* variable arises from geographic variation in border proximity as well as cross-time variation in the availability of payday loans owing to the emergence of payday stores in neighboring states. Furthermore, by including only zip codes in payday-banned states in the analyses, this identification strategy exploits plausibly exogenous variation in access to payday loans.

The model is estimated by the Poisson quasi-maximum likelihood estimator (QMLE). Under the mild condition that the conditional mean is correctly specified, this estimator provides consistent estimates, is fully robust to distributional misspecification, and does not require that the distribution be Poisson (Wooldridge, 1999).[22] In all regressions, unless described otherwise, standard errors are corrected to account for an arbitrary correlation at the county level.

Although this study mainly uses Poisson models, owing to the count nature of the inpatient data, as a robustness check, I also compare estimates from the OLS specifications of the following form:

$$\log\left(Y_{zct}\right) = \alpha_z + \beta Payday_{zt} + X'_{zt}\delta + Border_z \cdot t + \gamma_t + \eta_c \cdot t + \epsilon_{zt}, \qquad (2)$$

where Y_{zct} is an outcome measure and all other variables are defined as before.

4 Empirical Results

The results presented in this section suggest that access to payday loans increases suicide attempts. The analysis begins by investigating the effects of access to short-term high-interest loans on suicide attempts by all age groups. To examine the possible mechanisms for these effects further, I study the relationship of payday loans and suicide attempts in different demographic groups, such as age, race, sex, and insurance type. Finally, I provide evidence for mental health explanation as the channel through which credit access affects suicide risk.

4.1 Dynamic Effects

First, I show there was no differential trend across locations prior to gaining access to payday loans and that the effects are pronounced only for those aged under 65 years—the treated

[22]In addition to a consistent estimation of the count data models, the Poisson quasi-maximum likelihood method can be used to obtain consistent estimates for positive and continuous variables as long as the conditional mean is correctly specified (Wooldridge, 1999).

group—after obtaining access to payday loans. I estimate the following specification:

$$\mu_{zct} = \exp\left(\alpha_z + \sum_{s=-3(0)}^{3} \beta_s Payday_{z,t+s} + X'_{zt}\delta + Border_z \cdot t + \gamma_t + \eta_c \cdot t + \epsilon_{zt}\right), \qquad (3)$$

where μ_{zct} is the expected number of discharges of suicide attempts, and $Payday_{z,t+s}$ are six separate dummy variables set to one in the sth year before or after having access to payday loans, and zero otherwise. I do not include an indicator for the year in which payday lending was first allowed (or started to emerge), so β_t measure the dynamics of suicide attempts relative to the base years, denoted as year 0.

The top panel of Figure 4 shows the dynamic impact of access to payday loans on suicide attempts among those aged under 65 years. Although there is a slightly increasing trend of suicide attempts in the pre-payday periods, the point estimates are not statistically different from zero. A sharp increase can be observed after gaining access to payday loans, and there are relatively persistent effects over 3 years. The bottom panel displays the dynamic effects among the control group—the elderly. As can be seen, there is no pattern that is statistically significantly different from zero after gaining access to payday loans. As with previous results, the striking difference between the two age groups provides evidence for adverse effects of having access to payday loans on suicide attempts.

4.2 Baseline Empirical Results

Table 2 reports the baseline estimates of the effects of access to payday loans on attempted suicides. In all specifications, dependent variables are regressed on the binary payday access variable, county-specific time trends, border time trends, zip code fixed effects, and year fixed effects; and for all even-numbered columns, a set of zip code level economic controls are included in the estimations. Standard errors are adjusted to account for an arbitrary variance-covariance matrix at county level. The first two columns report estimates from a Poisson regression and all others, estimates from an OLS. All Poisson regressions used in this paper produce estimates, obtained by the Poisson QMLE with robust standard errors clustered by county, which are completely robust to arbitrary distributional misspecification and serial correlation.

Columns 1 and 2, estimated by Poisson regressions with suicide attempts as the dependent variable, report considerably similar estimates. Exponentiating the coefficients of 0.104 and 0.100, these results indicate that having access to payday loans increases attempted suicides by 11.0% and 10.5%, respectively.[23] Although adding controls slightly decreases the point estimate, the two estimates are of similar magnitude and the effects of payday loan access on attempted suicides are both statistically and economically significant.

As a quick robustness check, I compare these Poisson estimates with estimates from OLS specifications in columns 3 through 6. Columns 3 and 4 use the natural logarithm of the rate of attempted suicides as the dependent variable, where the rate of attempted suicides is calculated as the total number of attempted suicides per 100,000 people. Estimates from these specifications are very significant at the 1% significance level with slightly increased point estimates compared to Poisson specifications. Columns 5 and 6 replicate the previous two models with a slight adjustment for zero count of suicide attempt; that is, attempt counts are increased by 1, in order to keep zip codes with no suicide attempt. The estimates also are significant and quite similar in magnitude with the Poisson estimates.

Overall, the results imply that access to payday loans increases annual suicide attempts by 9.2–12.2%. Stable and consistent results across both Poisson and OLS specifications confirm that adjusting for observations with zero count and changing functional forms of the dependent variable have little effect on the interpretation of the estimated coefficient on *Payday*. If calculated at the mean rate (52.3 suicide attempts per 100,000 people), the baseline estimate (column 2) implies that gaining access to high-interest short-term loans causes an additional 5.5 suicide attempts per 100,000 people, which equates to 1,400

[23]Since each of these estimates is the log of the ratio of expected attempted suicide counts, a simple conversion is required to interpret them precisely; for example, the estimate from the second column, 0.100, is converted to $0.105\,(=\exp(0.100)-1)$.

additional suicide attempts for New York and New Jersey combined each year.[24]

A somewhat important item to check is how suicide *attempt* compares with suicide *mortality*. Table 3 reports the baseline estimates of the effects of access to payday loans on suicides *mortality*. Since mortality data are not available at zip level, the table reports county-level analyses. In general, the estimates are consistent with the zip-level counterparts, except that the size of the effects of payday access on suicide mortality is a bit larger than that on suicide attempts. [25]

4.3 How Does Access to Payday Loans Affect Borrowers Differently?

Prior studies have identified the characteristics of primary customers of paydays, for example, households with low to moderate income (Melzer (2011); Pew Charitable Trusts (2012)); those who are divorced or separated, disabled, or without a college degree (Pew Charitable Trusts, 2012); and military personnel (Carrell and Zinman, 2014). This subsection explores heterogeneous effects across diverse demographic groups and tests the hypotheses that people with higher demand for payday loans are more responsive to newly obtained access to payday loans; consequently, there are more suicide attempts in high demand zip codes. Base

4.3.1 Age

Since borrowers need to provide employment records and previous payrolls to payday lenders in order to be eligible for payday loans, I expect to see a pronounced impact of payday access among those aged under 65 years but not among the elderly who are retired. Although unemployed retirees who are mainly on Social Security might still qualify for payday loans,

[24]The calculation of 1400 additional attempts is based on the population from the decennial census 1990, in which New York and New Jersey have populations of 18 million and 7.7 million, respectively.

[25]The effects of payday access on suicide risks are 18.6% for suicide mortality and 10.5% for suicide attempts. This result might come from different characteristics between mortality and hospitalization due to suicide. Lethal methods of suicide, such as use of firearms and jumping from heights, do not require hospitalization if the attempters die on spot; thus, cases of this sort are not included in my suicide attempt data. In addition, suicide attempters who are initially hospitalized but die during or after treatments are included in the mortality data of this study.

not all payday loan lenders accept applications from them, possibly because there would be no wages to be garnished from them if a payment were missed. With these increased costs and possible stricter screening for retired applicants, there would be much less incentive for the elderly to travel to a payday lender. Indeed, a survey by Pew Charitable Trusts (2012) finds that the primary consumer group of payday loans is prime-age workers and only 2% of the elderly have used payday loans. As such, my approach naturally constructs a control group consisting of people aged 65 years and over.

Each column of Table 4 shows the effect of payday access on attempted suicide by different age groups. As expected, only estimates for the groups that are presumably affected by this credit type are significant and economically meaningful (columns 3–8). Even more convincing, perhaps, is that the effect increases with demand for this loan. In other words, the age group with the largest share of people who have used a payday loan (age 25–44 years) reports the biggest increase in suicide attempts, 16.3%, after gaining access to payday loans, followed by 12.6% and 12.0% for the age groups 25–54 years and 25–64 years, respectively.[26]

For the elderly (column 9) and younger groups (columns 1 and 2), however, the estimates are small and not statistically significant at any standard level.[27] Despite the fact that the estimate for the youngest group (column 1) is insignificant, this group is not a good control group. Because people aged under 19 years (or 20–24 years) are likely to live with parents who are in the range of age groups with high demand for payday loans, there is a possibility for a second order effect of payday loans. In other words, a suicide attempt or death by parents who suffered from debts from payday loans potentially could be followed by one by their children.[28] Even without an attempt by parents, if detrimental effects from payday

[26]See Pew Charitable Trusts (2012) for detailed reports on demographics of payday loan borrowers.

[27]During the period of the sample used, 1994–2000, the average mean rate of suicide attempts for the elderly was 24.6 per 100,000. One reason for such a low rate, compared with their highest suicide *mortality* rate, is that the elderly who commit suicide tend to use more lethal means due to ease of access and lower physical resilience than younger groups (Conwell et al., 2011). Since all of the specifications in this study include zip code fixed effects, the disparity between the rates of suicide *attempt* and *mortality* does not bias the estimates or harm the eligibility of the elderly as a control group, unless there is a systemic change of methods used for suicide attempts in response to payday loan access.

[28]Family history of suicide is among the top high-risk factors (Carrigan and Lynch, 2003).

loans worsen intra-family relationships or economic hardships, the risk of suicide for children could increase. Therefore, I prefer including the aged under 24 years in the treatment group for a more conservative analysis. Indeed, the regression results in this study hold regardless of inclusion of those aged under 24 years.

4.3.2 Sex

Table 5 explores heterogeneity of the effects of payday loans on suicide attempts across sex. The dependent variable of each column is the number of suicide attempts by a denoted group; for instance, in column 1, the dependent variable is the number of suicides by males aged under 65 years and, in column 2, by females aged under 65 years.

The results imply a 15.8% increase in attempted suicides for males aged under 65 years and an 8.7% increase for females aged under 65 years. Even though the effect of payday access for the younger male group is twice as large as that for the younger female group, because of the higher suicide attempt rate among females, the total expected additional discharges due to payday access are similar for both sexes: 5.8 additional patients for males and 4.5 for females. Columns 3 and 4 present estimates for the elderly. Although the point estimate for elderly males is positive, it is not statistically different from zero. Moreover, the estimate is even negative for elderly females.

4.3.3 Race

Table 6 reports estimates from specifications by race and age. Column 1 shows that having access to payday loans would increase attempted suicides among the white population aged under 65 years by 12.6% and an additional 5.4 discharges, while the white control group (aged 65 years and over) in column 2 has no significant effects. Columns 3 and 4 show estimates for the black population, and columns 5 and 6 for all minorities, including the black population. Although the point estimates for minorities under 65 years (columns 3 and 5) are similar in sizes with that for the white counterpart (column 1), they all have, as expected, positive signs and the estimates are negative and statistically insignificant for the elderly of both groups.[29]

4.3.4 Insurance

Since the primary target of payday lenders is the employed, who can provide a history of previous paychecks, a logical test we can run is to observe if the group of patients with private health insurance is disproportionately affected by access to payday loans.[30] Taking advantage of the detailed discharge-level inpatient data, I can use payer information. For each discharge record, I categorize the patient as having private health insurance if either the patient's primary or secondary payer is private insurance, and similarly for Medicaid and Medicare.[31] Discharges that are expected to be paid solely by the patients are categorized as self-pay; that is, either the primary or secondary payer is categorized as self-pay with none of them indicating other types of insurance.[32]

Table 7 reports the results. Only the estimate for patients with private insurance is statistically significant, showing a 13.2% increase in attempted suicides. Patients with Medicaid even have a negative estimate, although it is statistically not different from zero. In addition, the elderly is statistically insignificant. The negative and small effects of payday access for non-private insurance holders makes sense, because very low-income people and the elderly have no or very limited eligibility for payday loans.

4.3.5 Income

Table 8 tests whether zip codes with a high share of low- to moderate-income households that have high demand for payday loans are disproportionately affected by accessing payday loans. Elliehausen and Lawrence (2001) finds that individuals in the income range $25,000 to $50,000 are the main consumers of payday loans, accounting for more than half of the total

[29]Melzer (2011) also finds that payday access has significant effects on economic hardship for only the white population, with insignificant effects for other minority groups.

[30]In the U.S. over %80 of private health insurance is sponsored by employers.

[31]Private health insurance category includes Blue Cross, commercial carriers, and private HMOs and PPOs.

[32]A patient might be grouped into multiple insurance types because a non-trivial share of patients holds both private insurance and Medicare. However, the "self-pay" category is constructed as exclusive from other insurance types.

payday borrowers. Morse (2011) finds that those with income range of $15,000 to $45,000 have the largest probability of being financially constrained. With these prior findings, I use three income ranges for the test: household income in the range of $20,000 to $40,000, household income in the range of $12,000 to $50,000, and household income in the range of $20,000 to $50,000.

I split zip codes into those above and below the median share of household income in each range of income. For the income range $20,000–$40,000 in columns 1 and 2, a zip code is categorized as "Top 50 pct" if it has above the median share of households with income in the range $20,000–$40,000. Similarly, a "Bottom 50 pct" zip code has below the median share of households with income in the range $20,000–$40,000. The same construction method is used for columns 3–4 and columns 5–6 with household income ranges of $12,000–50,000 and $20,000–50,000, respectively. The estimates in all odd-numbered columns (top half percentile zips) report significant and large effects of payday access on attempted suicides, ranging from 15.0% to 20.8%, or 8.4 to 11.2 additional attempted suicides per 100,000. On the other hand, none of the even-numbered columns (bottom half percentile zips) report statistically significant estimates. Moreover, the point estimates are considerably smaller than the high demand zip codes.

4.3.6 Other Demand Factors

Table 9 reports estimates from a further test on the effects of payday access using other demand factors: single parents (columns 1–2), divorced people (columns 3–4) and high-school graduates (columns 5–6). Construction of the 'Top 50 pct" and "Bottom 50 pct" zip codes are the same as for Table 8; that is, based on the median share of each factor, I divide the sample into two subsamples and perform analyses within each subsample. As described earlier, all those characteristics have positive correlations with demand for payday loans.

The estimates from high-demand zip codes (odd-numbered columns) show that the effects are large; there is a 9.1–12.2% increase in suicide attempts after gaining access to payday loans in zip codes with more single parents, divorced people, and high-school graduates. In addition, the estimates mean an additional 5.4 to 7.3 discharges per 100,000 people. By contrast, there are no significant estimates for low-demand zip codes and the estimates are considerably small.

4.4 Mental Distress: The Channel through which Financial Distress Affects Suicide Risk

The existing literature suggests that stress is associated with deterioration in both physical and mental health (McEwen, 1998; Cooper, 2004; Schneiderman et al., 2005). If financial distress increases the overall stress level, we would expect that changes in household balance sheets would affect health and healthcare usage as well.[33] Several studies find support for this channel (e.g., Gross and Tobacman (2014); Evans and Moore (2011); Dobkin and Puller (2007); Parker et al. (2013); Currie and Tekin (2015)). As such, if accumulated household debts attributable to expensive credit worsen emotional and mental instability, then a member of the household who is at risk might develop suicidal ideation and could be located below his or her own suicide threshold. As a result, those who suffer from mental well-being deterioration might consult a doctor and obtain psychotropic drugs (antidepressants), such as Prozac.[34] With easier access to these psychotropic medications, suicidal borrowers are more likely to use prescribed psychotropic drugs as a method to commit suicide. This section provides a test for this mental health channel.

First, I briefly recalculate the main analyses (in Table 4 and Table 7) with a focus on suicide attempts by poisoning, instead of analyses on suicide attempts by all methods. Table 10 reports estimates of the effects of access to payday loans on attempted suicides by poisoning. As Panel A shows, gaining access to payday loans increases the number of suicide

[33]Indeed, Deaton (2011) finds that the collapse of Lehman Brothers had negative effects on self-reported worry, stress, and life evaluations of Americans.

[34]Fluoxetine, an antidepressant known mostly as Prozac, was first introduced in 1986 by Eli Lilly and Company. The drug was a commercial success. Prozac was the U.S.'s most prescribed antidepressant within 5 years of its introduction (Fitzpatrick, 2010). Because the patent of Prozac expired in August 2001, to minimize this impact, if any, which could bias the results of this research, I choose 1994–2000 as the sample period of this project.

attempts by poisoning only among the treatment group (those aged under 65 years) by 14.1% and does not affect the control group (those aged 65 years and over). Even more reassuring is that the point estimate for the control group is almost zero and even negative. The dynamic effects of payday access on suicide attempts by poisoning are displayed in Figure 5. The top panel shows the dynamic effects for the treated group, which is consistent with our previous findings. There are no pre-existing trends, but after gaining access to payday loans, there is a sudden increase in attempted suicides by poisoning. Unlike the younger neighbors, in the bottom panel, the older population's poisoning attempt indicates no discernible responses to payday loans.

Panel B of Table 10 describes the effects of payday access on suicide attempts by poisoning by different insurance holders. Not surprisingly, the only group significantly affected by payday loans is patients with private insurance, in other words, the employed who are the primary consumers of payday loans (column 1). The point estimate, which is statistically significant at the 1% level, indicates a 19.8% increase in hospitalization of employed people due to suicide attempts by poisoning. Patients with other insurance types do not have significant estimates. Because of the small share of self-paying patients who have no private insurance, Medicaid or Medicare, the majority of zip codes are dropped in the regressions owing to no variation in the dependent variable. In other words, there are no self-paying patients who have attempted to commit suicide by poisoning for many zip codes throughout the sample period. Therefore, with this small number of observations, the point estimate is highly imprecise. The dynamics of suicide attempts by poisoning by patients with a different insurance type (in Figure 6) provide additional support for the treatment-control interpretation; for all insurance-type patients, there are no pre-existing trends but a significant increase only for employed patients (with private insurance).

Finally, Table 11 provides the result for a test of the mental health channel. Patients with mental health deterioration due to financial distress will seek medical care through outpatient settings or physician's office visits and will use prescription drugs to treat depression, anxiety, and emotional distress. It is plausible that easier access to a means of suicide, or psychotropic drugs, raises the risk of suicide by overdosing on those drugs. Column 2 is the core test for the mental health channel. It indicates that there is a 21.9% increase in suicide-related hospitalization of those aged under 65 years by overdosing on psychotropic agents.[35] Unlike those aged under 65 years, there is no statistically significant effect for the elderly (in column 3) who have little access to payday loans. This confirms the hypothesis that mental health could be one of major driving forces behind suicide risk and financial distress caused by expensive credit. Column 5 reports that suicide attempts by other medicinal drugs increased by 14.3%. This result is expected, because suicidal people use both prescription and non-prescription drugs to commit suicide. The focal point of the test is to observe whether the treatment group uses more psychotropic drugs for poisoning (in column 2) and whether the control group has no statistically significant change (in column 3). For suicide attempts by poisoning with non-medicinal substances (e.g., petroleum products, acids, and lead compounds), columns 7–9 show no effects of access to payday loans.

4.5 Robustness Checks and a Placebo Test

Table 12 presents estimates from a diverse set of specifications as robustness tests. In Panel A, columns 1 and 2 are the baseline estimates (as in columns 8 and 9 of Table 4). Columns 3 and 4 show the coefficients of *payday* in specifications using a subset of the main sample, which includes zip codes with population greater than 1,000 in the 1990 census. Similarly, the specifications of columns 5 and 6 use a subsample that includes zip codes with population greater than 3,000. The estimates are all significant and similar in size with only the younger group's estimates being statistically and economically meaningful.

In Panel B, I perform a further robustness test with another set of subsamples. The subsample used in columns 1 and 2 includes zip codes that have a non-zero count of suicide attempts in each year for the entire sample period. Columns 3 and 4 use zip codes with

[35] Psychotropic drugs temporarily alter mood, perception, consciousness, and behavior and are prescribed as anti-depressants and anti-psychotics to treat mental illnesses.

at least 5 years of non-zero suicide attempts (out of 7 years), and finally, columns 5 and 6 use zip codes with at least 2 years of non-zero suicide attempts. Having all non-zero suicide attempts means the zip code is likely to have a large population size. Restricting the sample does not alter the interpretation of the previous findings. All estimates for the elderly group are statistically insignificant and small, whereas the treated younger group has significant, large, and stable estimates.

Panel C presents estimates from a falsification test using the following specification with placebo payday access assignment:

$$\mu_{zct} = \exp\left(\alpha_z + \beta FakePayday_{zt} + X'_{zt}\delta + Border_z \cdot t + \gamma_t + \eta_c \cdot t + \epsilon_{zt}\right), \tag{4}$$

where $FakePayday_{zt}$ equals one if a zip code in New York and New Jersey is within 25 miles of a border of payday-banning states (e.g., Vermont, Massachusetts, and Connecticut) after the emergence of payday lending in Pennsylvania and Delaware, and zero otherwise (See Figure 7). These zip codes with $FakePayday_{zt} = 1$ do *not* have real access to payday loans because none of their neighboring states allowed payday lending. As Panel C shows, the estimates are small and insignificant. The absence of significant effects of placebo payday access measure suggests that the relationship between access to payday loans and increased suicide attempts is not coincidental. The overall findings of this study, as well as the robustness tests, are difficult to be reconciled with alternative explanations for increases in suicide attempts by people aged under 65 years and the employed with private insurance.

5 Conclusion

This study analyzes the effects of access to payday loans on the long-term well-being of borrowers, measured by suicide risk. The robust evidence is consistent with payday loans increasing the risk of suicide for low- and moderate-income borrowers and employed workers. I find that having access to short-term, expensive payday loans increases hospitalization due to suicide attempts by 10%. This estimate implies at least an additional 5.5 hospitalized suicide attempts per 100,000 people and, if converted to the national level, an additional 15,000 attempts in 1998. As such, the results suggest that the social costs to increased suicide attempts and suicide deaths caused by gaining access to payday loans are quite large. At a minimum, suicide attempts incurred annual medical costs of $142 million per year during the late 1990s and early 2000s.

In addition, the findings provide a possible mechanism through which financial distress caused by expensive credit affects the suicide risk of a population. Due to access to payday loans, borrowers who accumulate excessive amount of debts undergo financial distress. This in turn causes their mental and emotional stability to deteriorate through stress. Mentally distressed people who have easier access to prescription medications, such as antidepressants, are more likely to attempt suicide by poisoning. Although this explanation cannot be tested directly on the extensive margin (new antidepressant prescriptions due to payday access), the finding cannot be explained by alternative explanations.

While the results presented in this study provide strong evidence for detrimental welfare consequences of having access to payday loans, this causal link should not be misinterpreted as a call for a complete ban on payday lending. The fact that 12 million Americans use payday loans per year indicates that there are no better alternatives for low- and moderate-income credit-constrained households. Thus, without fulfilling otherwise unmet demand, depriving already credit-constrained households of payday loans that serve as their last resort of lending will be a welfare-reducing policy. Hence, careful and thorough government intervention is required to regulate payday loans.

Appendix: CCS Single-Diagnosis Codes

- Suicide Attempt: CCS 662
- Poisoning by Psychotropic Agents: CCS 241
- Poisoning by Other Drugs: CCS 242
- Poisoning by Non-medicinal Substances: CCS 243
- Poisoning: CCS 241, 242, 243

References

Agarwal, S., P. M. Skiba, and J. Tobacman (2009). Payday loans and credit cards: New liquidity and credit scoring puzzles?

Barr, M. S. (2004). Banking the poor. *Yale Journal on Regulation 21*, 121–237.

Benjamin, D. J., O. Heffetz, M. S. Kimball, and A. Rees-Jones (2014). Can marginal rates of substitution be inferred from happiness data? evidence from residency choices. *The American economic review 104*(11), 3498–3528.

Bertrand, M. and S. Mullainathan (2001). Do people mean what they say? implications for subjective survey data. *The American Economic Review 91*(2), 67–72.

Bhutta, N. (2014). Payday loans and consumer financial health. *Journal of Banking & Finance 47*, 230–242.

Bhutta, N., P. Skiba, and J. Tobacman (2015). Payday loan choices and consequences. *Journal of Money, Credit and Banking 47*(2-3), 223–260.

Brickley, P. (1999). Bank teams up with 'payday lender'. *Philadelphia Business Journal*. Jul 5, 1999,http://philadelphia.bizjournals.com/philadelphia/stories/1999/07/05/story4.html.

Carrell, S. and J. Zinman (2014). In harm's way? payday loan access and military personnel performance. *Review of Financial Studies 27*(9), 2805–2840.

Carrigan, C. G. and D. J. Lynch (2003). Managing suicide attempts: guidelines for the primary care physician. *Primary care companion to the Journal of clinical psychiatry 5*(4), 169.

Carter, S. P. and W. Skimmyhorn (2016). Much ado about nothing? new evidence on the effects of payday lending on military members. *Review of Economics and Statistics* (0).

Case, A. and A. Deaton (2015). Suicide, age, and wellbeing: An empirical investigation. *National Bureau of Economic Research*.

Caskey, J. P. (2005). Fringe banking and the rise of payday lending. *Credit markets for the poor 17*, 18–19.

CFPB (2014). CFPB data point: Payday lending. *The CFPB Office of Research, March 2014*.

Conwell, Y., K. Van Orden, and E. D. Caine (2011). Suicide in older adults. *Psychiatric Clinics of North America 34*(2), 451–468.

Cooper, C. (2004). *Handbook of stress medicine and health*. CRC Press.

Currie, J. and E. Tekin (2015). Is there a link between foreclosure and health? *American Economic Journal: Economic Policy 7*(1), 63–94.

Daly, M. C., A. J. Oswald, D. Wilson, and S. Wu (2011). Dark contrasts: The paradox of high rates of suicide in happy places. *Journal of Economic Behavior & Organization 80*(3), 435–442.

Daly, M. C. and D. J. Wilson (2009). Happiness, unhappiness, and suicide: An empirical assessment. *Journal of the European Economic Association 7*(2-3), 539–549.

Daly, M. C., D. J. Wilson, and N. J. Johnson (2013). Relative status and well-being: evidence from us suicide deaths. *Review of Economics and Statistics 95*(5), 1480–1500.

Deaton, A. (2011). The financial crisis and the well-being of america. In *Investigations in the Economics of Aging*, pp. 343–368. University of Chicago Press.

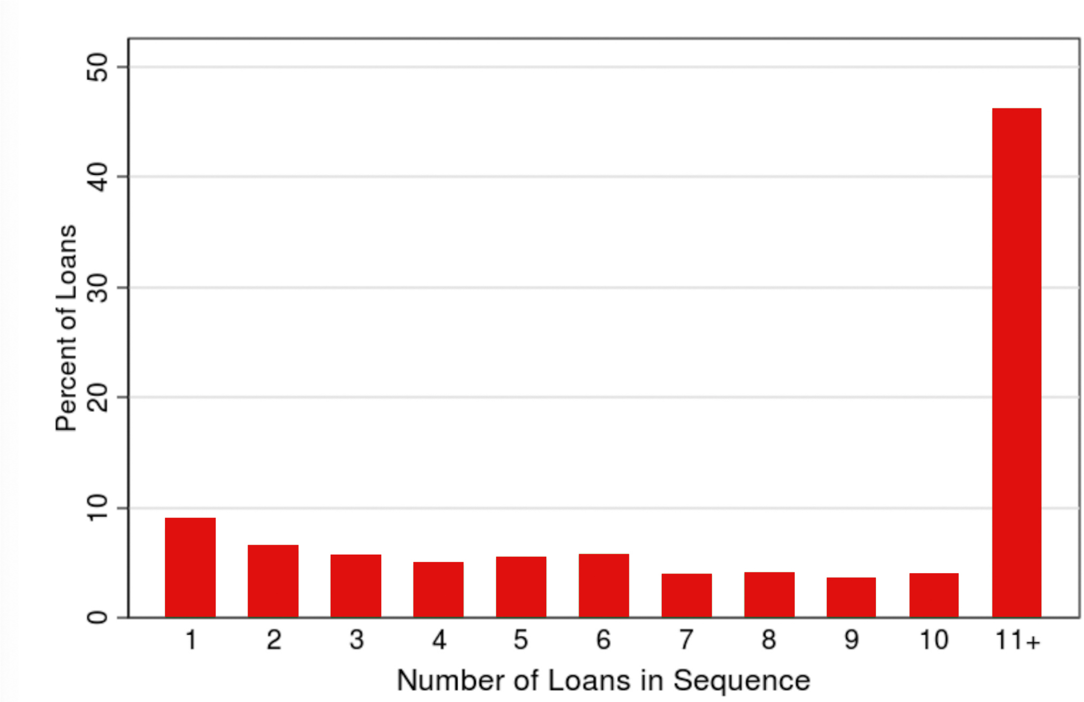
Deaton, A. and A. A. Stone (2013). Two happiness puzzles. *The American economic re-*

view 103(3), 591–597.
Dobkin, C. and S. L. Puller (2007). The effects of government transfers on monthly cycles in drug abuse, hospitalization and mortality. *Journal of Public Economics 91*(11), 2137–2157.
Elliehausen, G. and E. C. Lawrence (2001). Payday advance credit in america: An analysis of customer demand. *Credit Research Center, Georgetown University*, 39–40.
Evans, W. N. and T. J. Moore (2011). The short-term mortality consequences of income receipt. *Journal of Public Economics 95*(11), 1410–1424.
Evans, W. N. and T. J. Moore (2012). Liquidity, economic activity, and mortality. *Review of Economics and Statistics 94*(2), 400–418.
Fitzpatrick, L. (2010). A brief history of antidepressants. *Time*. Jan. 07, 2010.
Flannery, M. J. and K. Samolyk (2005). Payday lending: Do the costs justify the price? *FDIC Center for Financial Research Working Paper* (2005/09).
Fox, J. A. (1998). The growth of legal loan sharking: a report on the payday loan industry. *Washington, DC: Consumer Federation of America.*
Fox, J. A. (1999). Safe harbor for usury: Recent developments in payday lending. *Advancing the Consumer Interest 11*(2/1), 7–12.
Fox, J. A., M. Gordon, and L. Borja (1997). High cost of 'banking' at the corner check casher: Check cashing outlet fees and payday loans. *Consumer Federation of America.*
Fox, J. A. and E. Mierzwinski (2000). Show me the money! a survey of payday lenders and review of payday lender lobbying in state legislatures. *US PIRG and Consumer Federation of America. February.*
Gerdtham, U.-G. and M. Johannesson (2003). A note on the effect of unemployment on mortality. *Journal of health economics 22*(3), 505–518.
Granados, J. A. T. (2005). Increasing mortality during the expansions of the us economy, 1900–1996. *International journal of epidemiology 34*(6), 1194–1202.
Gross, T. and J. Tobacman (2014). Dangerous liquidity and the demand for health care evidence from the 2008 stimulus payments. *Journal of Human Resources 49*(2), 424–445.
Hamermesh, D. S. and N. M. Soss (1974). An economic theory of suicide. *Journal of Political Economy 82*(1), 83–98.
Han, S., B. J. Keys, and G. Li (2015). Information, contract design, and unsecured credit supply: Evidence from credit card mailings.
Han, S. and W. Li (2007). Fresh start or head start? the effects of filing for personal bankruptcy on work effort. *Journal of Financial Services Research 31*(2), 123–152.
HCUP (2010). Clinical classifications software (ccs) for icd-9-cm. *Rockville, MD: Agency for Healthcare Research and Quality.*
Helliwell, J. F. (2007). Well-being and social capital: Does suicide pose a puzzle? *Social indicators research 81*(3), 455–496.
Henry, A. F. and J. F. Short (1954). *Suicide and homicide: Some economic, sociological and psychological aspects of aggression*, Volume 91442. Free Press New York.
Jagtiani, J. and W. Li (2015). Credit access after consumer bankruptcy filing: new evidence. *Am. Bankr. LJ 89*, 327.
Kahneman, D. and A. B. Krueger (2006). Developments in the measurement of subjective well-being. *The journal of economic perspectives 20*(1), 3–24.
Karger, H. J. (2005). *Shortchanged: Life and debt in the fringe economy.* Berrett-Koehler

Publishers.
King, U., W. Li, D. Davis, and K. Ernst (2005). Race matters: The concentration of payday lenders in african-american neighborhoods in north carolina. *Center for Responsible Lending 22*.
Kposowa, A. J. (2001). Unemployment and suicide: a cohort analysis of social factors predicting suicide in the us national longitudinal mortality study. *Psychological medicine 31*(01), 127–138.
Krueger, A. B. and D. A. Schkade (2008). The reliability of subjective well-being measures. *Journal of public economics 92*(8), 1833–1845.
Lee, J. (2017). Happiness puzzle: Well-being and suicide risks. *Working paper*.
Luo, F., C. S. Florence, M. Quispe-Agnoli, L. Ouyang, and A. E. Crosby (2011). Impact of business cycles on us suicide rates, 1928-2007. *American journal of public health 101*(6), 1139–1146.
McEwen, B. S. (1998). Protective and damaging effects of stress mediators. *New England journal of medicine 338*(3), 171–179.
Melzer, B. T. (2011). The real costs of credit access: Evidence from the payday lending market. *The Quarterly Journal of Economics 126*(1), 517–555.
Morgan, D. P. and M. R. Strain (2008). Payday holiday: How households fare after payday credit bans. *FRB of New York Staff Report* (309).
Morgan, D. P., M. R. Strain, and I. Seblani (2012). How payday credit access affects overdrafts and other outcomes. *Journal of Money, Credit and Banking 44*(2-3), 519–531.
Morse, A. (2011). Payday lenders: Heroes or villains? *Journal of Financial Economics 102*(1), 28–44.
Mortensen, P. B., E. Agerbo, T. Erikson, P. Qin, and N. Westergaard-Nielsen (2000). Psychiatric illness and risk factors for suicide in denmark. *The Lancet 355*(9197), 9–12.
Oswald, A. J. (1997). Happiness and economic performance. *The Economic Journal 107*(445), 1815–1831.
Parker, J. A., N. S. Souleles, D. S. Johnson, and R. McClelland (2013). Consumer spending and the economic stimulus payments of 2008. *The American Economic Review 103*(6), 2530–2553.
Parsons, C. A. and E. D. Van Wesep (2013). The timing of pay. *Journal of Financial Economics 109*(2), 373–397.
Pew Charitable Trusts (2012). Payday lending in america: Who borrows, where they borrow, and why.
Pierce, J. R. and P. K. Schott (2015). Trade liberalization and mortality: Evidence from us counties. Technical report, Yale mimeo.
Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics 115*(2), 617–650.
Schneiderman, N., G. Ironson, and S. D. Siegel (2005). Stress and health: psychological, behavioral, and biological determinants. *Annu. Rev. Clin. Psychol. 1*, 607–628.
Skiba, P. M. and J. Tobacman (2009). Do payday loans cause bankruptcy? *Vanderbilt Law and Economics Research Paper* (11-13).
Stegman, M. A. (2007). Payday lending. *The Journal of Economic Perspectives 21*(1), 169–190.
Stevenson, B. and J. Wolfers (2006). Bargaining in the shadow of the law: Divorce laws and

family distress. *The Quarterly Journal of Economics*, 267–288.
Wilkinson, W. (2007). In pursuit of happiness research: Is it reliable? what does it imply for policy? *What does it imply for policy*.
Wooldridge, J. M. (1999). Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics 90*(1), 77–97.
Zaki, M. (2016). Access to short-term credit and consumption smoothing within the paycycle.
Zinman, J. (2010). Restricting consumer credit access: Household survey evidence on effects around the oregon rate cap. *Journal of banking & finance 34*(3), 546–556.
Zinman, J. (2014). Consumer credit: Too much or too little (or just right)? *The Journal of Legal Studies 43*(S2), S209–S237.

Figure 1: Distribution of Number of Loans by Sequence



Notes: This figure is from a report by the Consumer Financial Protection Bureau (CFPB, 2014). It shows the distribution of the number of loans by sequence. For instance, a first loan in sequence indicates a new loan, and a fifth loan in sequence indicates that four renewals (rollovers) have been made on the initial loan. Approximately half the total loans are in the 10th or more sequence.

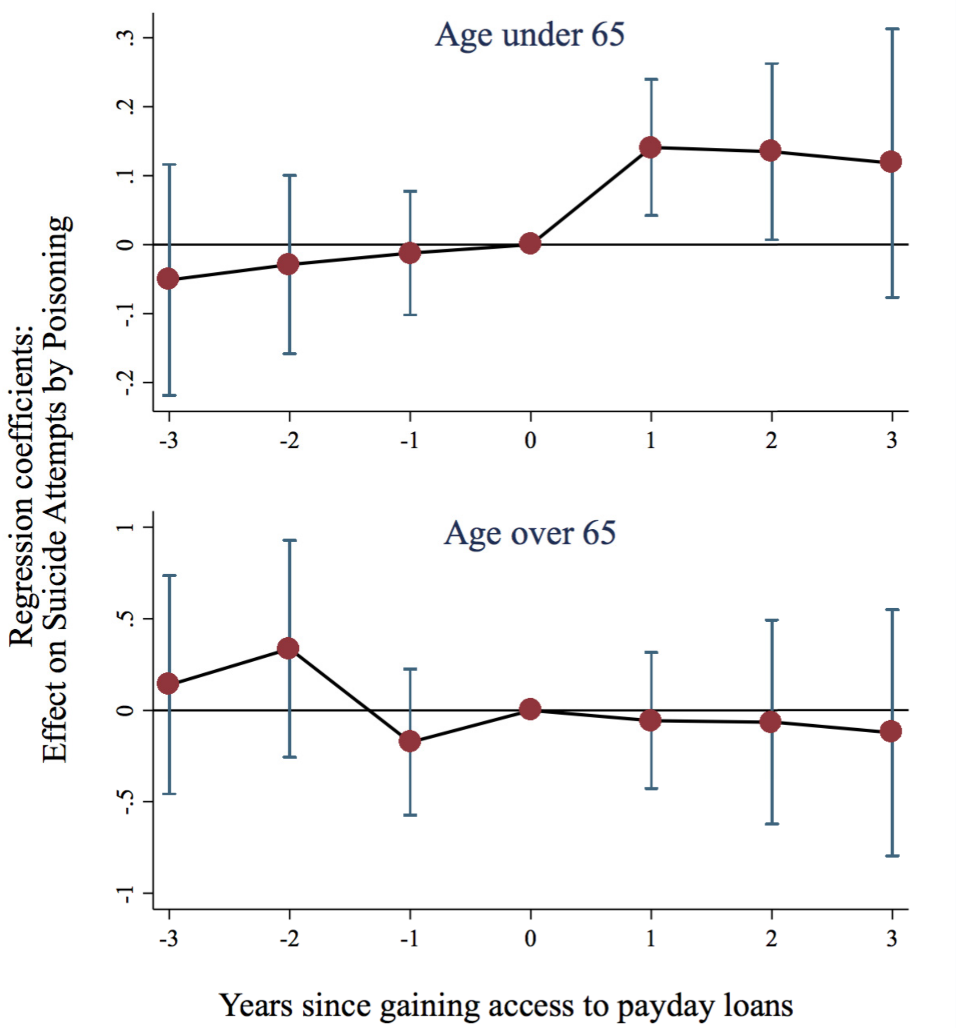
Figure 2: A Map of Northeastern States

Notes: Pennsylvania (PA) and Delaware (DE) are the only two payday-allowing states that share borders with New York (NY) and New Jersey (NJ) during the years 1994–2000. No other neighboring states to New York and New Jersey allowed payday lending during the sample period 1994–2000.

Figure 3: Zip Codes with Close Proximity to Payday-Allowing States

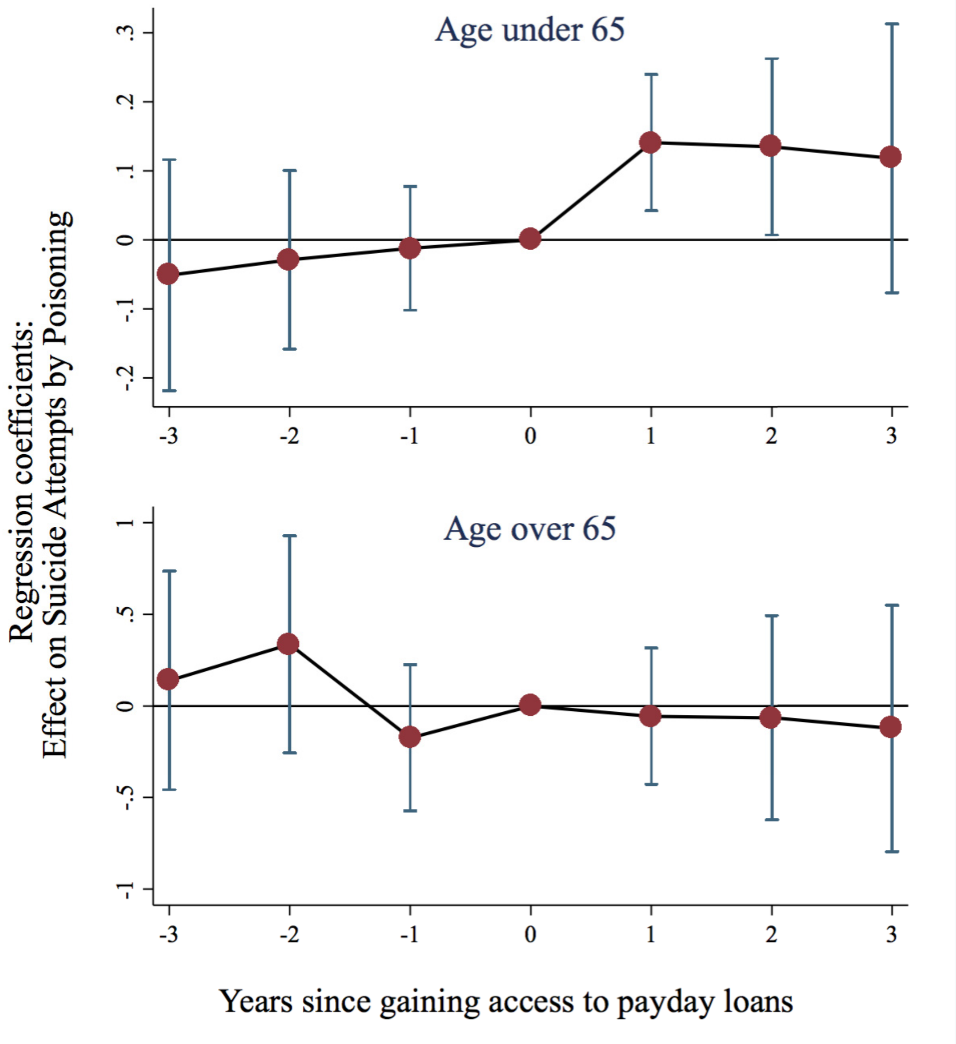
Notes: The shaded area represents zip code areas that are within 25 miles of the borders of Pennsylvania (PA) and Delaware (DE). The identification strategy assumes that populations in those zip codes have access to payday loans only after the emergence of payday lending in PA and DE, and that all other populations in zip codes in New York and New Jersey do not have access to payday loans during 1994–2000.

Figure 4: Dynamic Effects of Access to Payday Loans on Suicide Attempts



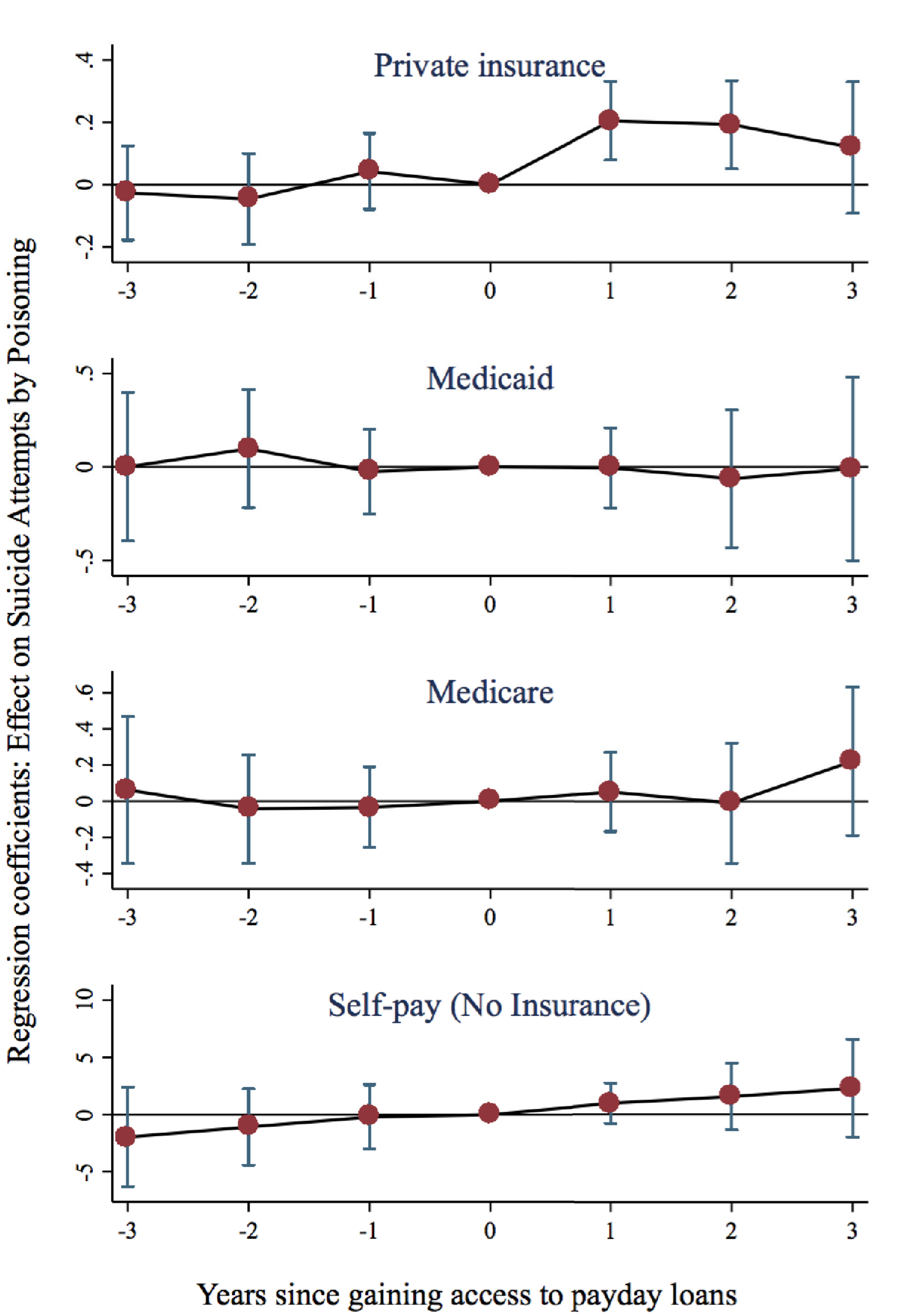
Notes: Each figure plots coefficients from regressions of suicide attempts on a series of indicator variables, including 3 years before and 3 years after gaining access to payday loans, as well as zip code-level controls, year fixed effects, zip code fixed effects, border trends, and county-specific trends. The vertical I-beams represent the 95% confidence interval. All estimates are by the Poisson quasi-maximum likelihood estimator (QMLE) with robust standard errors clustered by county.

Figure 5: Dynamic Effects of Access to Payday Loans on Suicide Attempts by Poisoning



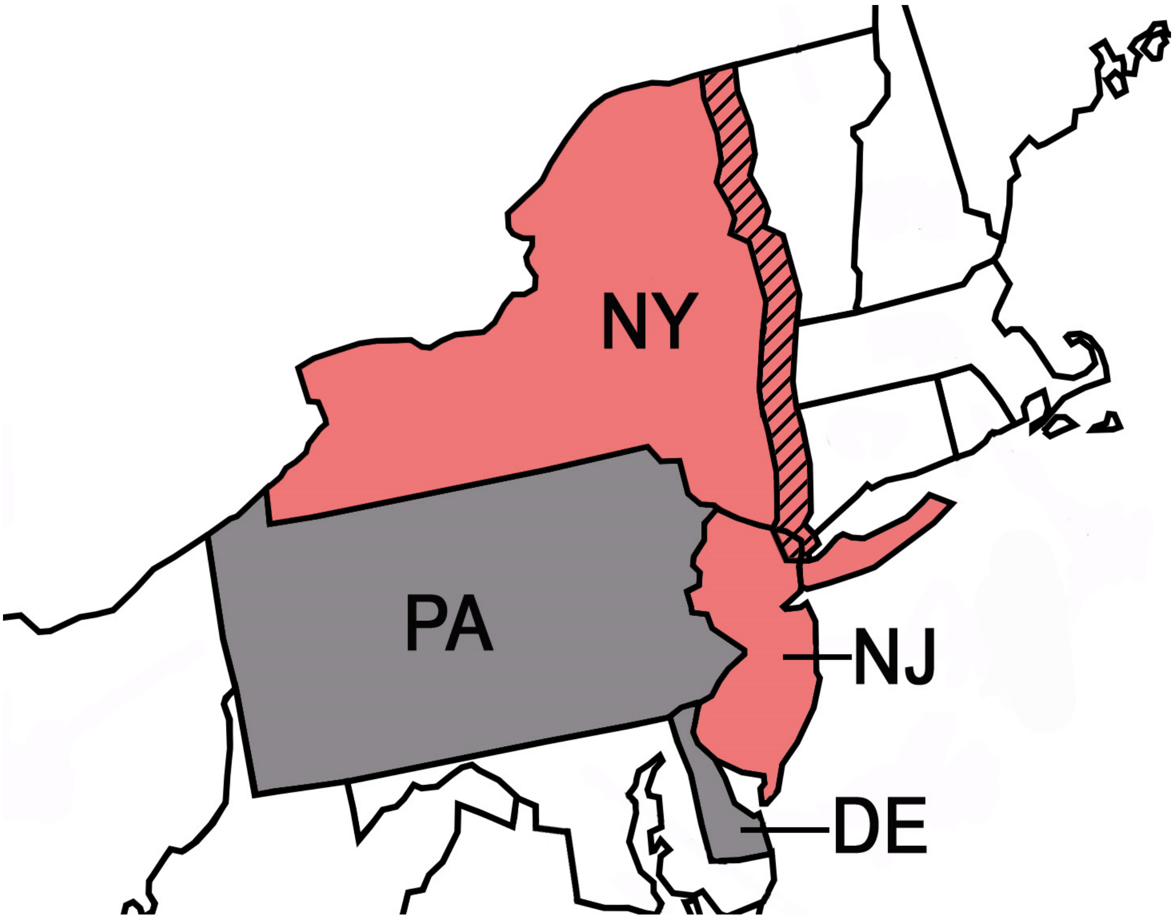
Note: Each figure plots coefficients from regressions of suicide attempts on a series of indicator variables, including 3 years before and 3 years after gaining access to payday loans, as well as zip code-level controls, year fixed effects, zip code fixed effects, border trends, and county-specific trends. The vertical I-beams represent the 95% confidence interval. All estimates are by the Poisson quasi-maximum likelihood estimator (QMLE) with robust standard errors clustered by county.

Figure 6: Dynamic Effects of Access to Payday Loans on Suicide Attempts by Poisoning



Notes: Each figure plots coefficients from regressions of suicide attempts on a series of indicator variables, including 3 years before and 3 years after gaining access to payday loans, as well as zip code-level controls, year fixed effects, zip code fixed effects, border trends, and county-specific trends. The vertical I-beams represent the 95% confidence interval. All estimates are by the Poisson quasi-maximum likelihood estimator (QMLE) with robust standard errors clustered by county.

Figure 7: Zip Codes with Close Proximity to Payday-Banning States: a Placebo Test



Notes: The shaded area represents zip code areas that are within 25 miles of the borders of payday-*banning* states (e.g., Vermont, Massachusetts, and Connecticut). Even after the emergence of payday lending in Pennsylvania and Delaware, these zip codes do *not* have real access to payday loans because none of their neighboring states allowed payday lending.

Table 1: Summary Statistics

	Payday Border = 1			Payday border = 0		
	Mean	Obs	Std. Dev.	Mean	Obs	Std. Dev.
Zip code demographics						
Population	19,450	2,618	12,777	34,553	12,215	23,457
Income per capita	16,615	2,618	5,441	17,240	12,215	8,740
Median household income	39,462	2,618	12,772	37,305	12,215	14,962
White (%)	0.87	2,618	0.18	0.74	12,215	0.28
Black (%)	0.09	2,618	0.15	0.16	12,215	0.23
All minorities (%)	0.13	2,618	0.18	0.26	12,215	0.28
Male (%)	0.49	2,618	0.24	0.48	12,215	0.24
Female (%)	0.51	2,618	0.24	0.52	12,215	0.24
High school dropouts (%)	0.21	2,618	0.09	0.26	12,215	0.12
High school graduates (%)	0.33	2,618	0.07	0.30	12,215	0.07
College graduates (%)	0.46	2,618	0.14	0.45	12,215	0.15
Married (%)	0.59	2,618	0.08	0.54	12,215	0.09
Divorced (%)	0.07	2,618	0.02	0.06	12,215	0.02
Zip code business patterns						
Number of establishments	488	2,603	397	789	12,137	796
Number of employees	7,460	2,513	7,568	10,853	11,755	14,129
Annual payroll (per employee)	27,984	2,513	8,779	28,342	11,755	9,032
Discharge rates (per 100,000 people)						
Suicide attempts	62.2	2,618	33.3	50.9	12,215	34.9
Poisoning (non-medicinal substances)	2.2	2,618	2.5	2.1	12,215	8.6
Poisoning (psychotropic drugs)	23.2	2,618	13.5	16.0	12,215	12.5
Poisoning (other drugs)	32.1	2,618	17.1	26.0	12,215	19.1

Notes: Annual payroll is calculated as the zip code-level aggregate payroll divided by the number of employees. A discharge rate is calculated as an annual average of each discharge type by zip code for the sample period, 1994–2000. Means are weighted by zip code population in 1990. Sources: zip code demographics are from the Decennial Census 1990, the zip code-level business pattern data are from the County Business Patterns, and discharge rates are based on HCUP–New York and New Jersey State Inpatient Databases (SID) 1994–2000.

Table 2: Relationship Between Suicide Attempts and Payday Access

This table represents zip code-level regressions of suicide attempts on the payday access indicator. In columns 1 and 2, the Poisson models are estimated by the Poisson quasi-maximum likelihood estimator (QMLE). In columns 3–6, the models are estimated by ordinary least squares (OLS). "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits coefficients of border trends, county-specific trends, zip code fixed effects and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) Suicide attempts	(2) Suicide attempts	(3) ln(rate of suicide attempts)	(4) ln(rate of suicide attempts)	(5) ln(rate of 1+ suicide attempts)	(6) ln(rate of 1+ suicide attempts)
	Poisson		OLS		OLS	
payday	0.104**	0.100**	0.122***	0.108***	0.101**	0.092**
	(0.045)	(0.044)	(0.045)	(0.041)	(0.041)	(0.038)
log(wage)		0.003		-0.078		-0.042
		(0.056)		(0.064)		(0.051)
log(employment)		0.037		0.025		0.009
		(0.055)		(0.050)		(0.036)
log(establishment)		0.110		0.015		0.043
		(0.150)		(0.146)		(0.112)
total any discharges (per 1000)		0.000		0.006***		0.005***
		(0.000)		(0.001)		(0.001)
Effects of payday access	11.0%	10.5%	12.2%	10.8%	10.1%	9.2%
Average suicide attempts (per 100k)	52.3	52.3	52.3	52.3	52.3	52.3
Additional suicide attempts (per 100k)	5.7	5.5	6.4	5.6	5.3	4.8
Observations	14,063	13,662	10,916	10,796	14,833	14,268
Number of zip	2,009	1,976	2,009	1,978	2,119	2,086
Controls		X		X		X
Border Trends	X	X	X	X	X	X
County Trends	X	X	X	X	X	X
ZIP FEs & Year FEs	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 3: Relationship Between Suicide Mortality and Payday Access

This table represents county-level regressions of suicide deaths on the payday access indicator. In columns 1 and 2, the Poisson models are estimated by the Poisson quasi-maximum likelihood estimator (QMLE). In columns 3 and 4, the models are estimated by ordinary least squares (OLS). "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide deaths, and for columns 3 and 4, it is just the estimated coefficient of the "payday" variable. "Average suicide deaths (per 100,000)" is the average rate of suicide deaths. "Additional suicide deaths (per 100,000)" is the percentage change in the expected number of suicide deaths, attributable to access to payday loans. To save space, this table omits coefficients of border trends, county fixed effects, and year fixed effects. The data used to produce this table are the restricted version of compressed mortality files provided by the National Center for Health Statistics (NCHS). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1) Suicide deaths	(2) Suicide deaths	(3) ln(rate of suicide deaths)	(4) ln(rate of suicide deaths)
	Poisson		OLS	
Payday	0.168***	0.171***	0.185***	0.191***
	(0.051)	(0.050)	(0.056)	(0.056)
Unemployed		-0.018		-0.020
		(0.018)		(0.020)
log(income)		-0.017		0.090
		(0.457)		(0.458)
Effects of payday access	18.3%	18.6%	18.5%	19.1%
Average suicide deaths (per 100,000)	7.0	7.0	7.0	7.0
Additional suicide deaths (per 100,000)	1.3	1.3	1.3	1.3
Observations	283	283	283	283
Number of counties	44	44	44	44
Controls		X		X
County trends	X	X	X	X
County fixed effects & Year fixed effects	X	X	X	X
Cluster	county	county	county	county

Table 4: Relationship Between Suicide Attempts and Payday Access: by Age

This table represents zip-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts by the denoted age group. "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID) provided by the Agency for Healthcare Research and Quality (AHRQ). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) Aged under 19	(2) 20–24	(3) 25–44	(4) 25–54	(5) 25–64	(6) Under 45	(7) Under 55	(8) Under 65	(9) 65 and over
Payday	0.086	0.054	0.151***	0.119**	0.113**	0.134***	0.114***	0.109**	0.018
	(0.088)	(0.107)	(0.047)	(0.049)	(0.047)	(0.040)	(0.044)	(0.042)	(0.177)
log(wage)	-0.038	0.055	0.029	-0.001	0.003	0.005	-0.012	-0.008	0.025
	(0.104)	(0.131)	(0.096)	(0.084)	(0.076)	(0.081)	(0.074)	(0.069)	(0.190)
log(employment)	0.046	0.027	0.022	0.023	0.050	0.033	0.032	0.052	-0.112
	(0.118)	(0.101)	(0.058)	(0.058)	(0.058)	(0.053)	(0.055)	(0.056)	(0.191)
log(establishment)	0.133	0.484*	0.123	0.103	0.039	0.110	0.093	0.043	0.483*
	(0.224)	(0.272)	(0.163)	(0.153)	(0.155)	(0.152)	(0.145)	(0.149)	(0.278)
Total number of discharges (per 1,000)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Effects of payday access	9.0%	5.5%	16.3%	12.6%	12.0%	14.3%	12.1%	11.5%	1.8%
Average suicide attempts (per 100,000)	38.6	84.9	75.6	70.9	62.7	51.8	52.3	49.4	24.6
Additional suicide attempts (per 100,000)	3.5	4.7	12.3	9.0	7.5	7.4	6.3	5.7	0.4
Observations	11,901	10,096	12,835	13,176	13,255	13,370	13,529	13,563	8,252
Number of zip codes	1,713	1,450	1,850	1,900	1,912	1,931	1,955	1,960	1,183
Controls	X	X	X	X	X	X	X	X	X
Border trends	X	X	X	X	X	X	X	X	X
County trends	X	X	X	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X	X	X	X
Cluster	county	county	county	county	county	county	county	county	county

Table 5: Relationship Between Suicide Attempts and Payday Access: by Age and Sex

This table represents zip-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts by the denoted age–sex group. "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)
	Aged under 65		Aged 65 and over	
	male	female	male	female
Payday	0.147***	0.083*	0.082	-0.029
	(0.050)	(0.050)	(0.223)	(0.209)
log(wage)	-0.005	-0.007	-0.238	0.243
	(0.079)	(0.081)	(0.303)	(0.247)
log(employment)	-0.067	0.123*	-0.242	-0.075
	(0.062)	(0.072)	(0.262)	(0.201)
log(establishment)	0.005	0.073	0.241	0.531
	(0.197)	(0.157)	(0.408)	(0.388)
Total number of discharges (per 1,000)	0.000	0.001	0.007***	0.000
	(0.000)	(0.000)	(0.002)	(0.000)
Effects of payday access	15.8%	8.7%	8.5%	-2.9%
Average suicide attempts (per 100,000)	36.6	52.2	25.6	22.2
Additional suicide attempts (per 100,000)	5.8	4.5	2.2	-0.6
Observations	12,274	13,137	6,095	6,655
Number of zip codes	1,766	1,894	874	953
Controls	X	X	X	X
Border trends	X	X	X	X
County trends	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X
Cluster	county	county	county	county

Table 6: Relationship Between Suicide Attempts and Payday Access: by Race

This table represents zip-level regressions of suicide attempts on the payday access indicator. The dependent variable of each column is the number of suicide attempts by the denoted age–race group. “Effects of payday access” is the exponentiated coefficient of the “payday” variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. “Average suicide attempts (per 100,000)” is the average rate of suicide attempts in the denoted group. “Additional suicide attempts (per 100,000)” is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	White		Black		All Minority	
	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over
Payday	0.119***	0.053	0.144	-0.519	0.101	-0.501
	(0.046)	(0.184)	(0.149)	(0.553)	(0.094)	(0.606)
log(wage)	0.085	0.157	-0.169	-0.795	-0.170**	0.010
	(0.081)	(0.217)	(0.161)	(1.028)	(0.085)	(0.432)
log(employment)	0.072	-0.178	0.255*	0.712	0.024	0.015
	(0.066)	(0.195)	(0.151)	(0.777)	(0.079)	(0.505)
log(establishment)	0.098	0.729**	-0.525**	-0.437	-0.022	-0.445
	(0.129)	(0.295)	(0.262)	(1.784)	(0.220)	(0.839)
Total number of discharges per 1,000	0.000	0.000	0.000	0.016**	0.000	0.012**
	(0.000)	(0.001)	(0.000)	(0.007)	(0.000)	(0.005)
Effects of payday access	12.6%	5.4%	15.5%	-40.5%	10.6%	-39.4%
Average suicide attempts (per 100,000)	42.4	23.3	46.0	13.6	61.4	30.7
Additional suicide attempts (per 100,000)	5.4	1.3	7.1	-5.5	6.5	-12.1
Observations	13,457	7,695	5,650	1,057	7,790	2,225
Number of zip codes	1,944	1,103	810	151	1,117	319
Controls	X	X	X	X	X	X
Border trends	X	X	X	X	X	X
County trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 7: Relationship Between Suicide Attempts and Payday Access: by Insurance Type

This table represents zip-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts by patients of the denoted insurance type. "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) Private insurance	(2) Medicaid	(3) Medicare
Payday	0.124**	-0.046	0.072
	(0.058)	(0.093)	(0.089)
log(wage)	-0.029	0.031	0.066
	(0.082)	(0.108)	(0.147)
log(employment)	0.099	0.056	-0.056
	(0.068)	(0.096)	(0.120)
log(establishment)	0.131	-0.210	0.128
	(0.139)	(0.216)	(0.216)
Total number of discharges per 1,000	0.000**	0.001	0.002
	(0.000)	(0.001)	(0.001)
Effects of payday access	13.2%	-4.5%	7.5%
Observations	12,874	11,238	10,391
Number of zip codes	1,856	1,615	1,492
Controls	X	X	X
County trends	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X
Cluster	county	county	county

Table 8: Relationship Between Suicide Attempts and Payday Access: by Household Income

This table represents zip-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts by the denoted characteristics of zip codes. I split zip codes into those above ("Top 50 pct") and below ("Bottom 50 pct") the median share of household income in three income ranges: \$20,000–\$40,000, \$12,000–\$50,000, and \$20,000–\$50,000. For example, column 1 is a regression among zip codes whose share of household income in the range of \$20,000–\$40,000 is above the median share of that income range. The median share of household income for \$20,000–\$40,000 range is 0.28, \$12,5000–\$50,000 is 0.51, and \$20,000–\$50,000 is 0.40 (the Decennial Census 1990). "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of households w/ Income \$20,000–\$40,000		Share of households w/ Income \$12,000–\$50,000		Share of households w/ Income \$20k-\$50k	
	Top 50 pct	Bottom 50 pct	Top 50 pct	Bottom 50 pct	Top 50 pct	Bottom 50 pct
Payday	0.159**	0.053	0.140**	0.057	0.189***	0.033
	(0.072)	(0.058)	(0.071)	(0.060)	(0.058)	(0.059)
log(wage)	-0.005	-0.008	-0.005	-0.010	0.040	-0.028
	(0.105)	(0.074)	(0.093)	(0.076)	(0.093)	(0.069)
log(employment)	0.020	0.037	0.068	0.011	0.032	0.037
	(0.080)	(0.073)	(0.073)	(0.076)	(0.076)	(0.083)
log(establishment)	0.210	-0.001	0.162	0.009	0.258	-0.072
	(0.187)	(0.196)	(0.172)	(0.200)	(0.183)	(0.225)
Total number of discharges per 1,000	0.000	0.003**	0.000	0.004***	0.000	0.004**
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
Effects of payday access	17.2%	5.4%	15.0%	5.9%	20.8%	3.4%
Average suicide attempts (per 100,000)	56.0	50.4	56.2	50.6	53.9	51.5
Additional suicide attempts (per 100,000)	9.7	2.7	8.4	3.0	11.2	1.7
Observations	6,540	7,063	6,506	7,097	6,540	7,004
Number of zip codes	955	1,018	953	1,020	955	1,011
Controls	X	X	X	X	X	X
Border & county trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 9: Relationship Between Suicide Attempts and Payday Access: by Other Demand Factors

This table represents zip-level regressions of suicide attempts on the payday access indicator. The dependent variable of each column is the number of suicide attempts by the denoted characteristics group. For each demand factor, "Top 50 pct" ("Bottom 50 pct") zip codes have above (below) the median share of each demand factor. The median share of single parents in zip code level is 0.05, that for divorced people is 0.06, and that for high-school graduates is 0.34 (the Decennial Census 1990). "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of single parents		Share of divorced people		Share of high school graduates	
	Top 50 pct	Bottom 50 pct	Top 50 pct	Bottom 50 pct	Top 50 pct	Bottom 50 pct
Payday	0.115**	0.064	0.087*	0.075	0.107*	0.084
	(0.059)	(0.068)	(0.048)	(0.096)	(0.056)	(0.058)
log(wage)	-0.076	-0.003	-0.048	0.048	-0.014	0.018
	(0.050)	(0.110)	(0.051)	(0.123)	(0.098)	(0.069)
log(employment)	-0.098	0.137	-0.016	0.084	0.067	-0.010
	(0.087)	(0.089)	(0.082)	(0.080)	(0.070)	(0.078)
log(establishment)	-0.228	0.343**	-0.065	0.130	0.207	0.103
	(0.213)	(0.153)	(0.213)	(0.164)	(0.176)	(0.256)
Total numberdischarges per 1,000	0.006***	0.000*	0.006***	0.000*	0.000	0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Effects of payday access	12.2%	6.6%	9.1%	7.8%	11.3%	8.8%
Average suicide attempts (per 100,000)	59.8	43.7	59.8	44.3	59.0	43.4
Additional discharges (per 100,000)	7.3	2.9	5.4	3.5	6.7	3.8
Observations	6,853	6,750	6,905	6,705	6,667	6,943
Number of zip codes	995	978	998	976	972	1,002
Controls	X	X	X	X	X	X
Border trends	X	X	X	X	X	X
County trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 10: Relationship Between Suicide Attempts (Poisoning) and Payday Access: by Age and Insurance Type

This table represents zip code-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts (by poisoning) by patients of the denoted age group (Panel A) or insurance type (Panel B). "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of controls, border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: By Age Category

	(1) All population	(2) Aged under 65	(3) Aged 65 and over
Payday	0.127***	0.132***	-0.008
	(0.047)	(0.046)	(0.193)
Effects of payday access	13.5%	14.1%	-0.9%
Average suicide attempts (per 100,000)	40.6	44.5	15.7
Additional discharges (per 100,000)	5.5	6.3	-0.1
Observations	13,522	13,487	7,308
Number of zip codes	1,952	1,947	1,047
Controls	X	X	X
Border trends	X	X	X
County trends	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X
Cluster	county	county	county

Table 10: Relationship Between Suicide Attempts (Poisoning) and Payday Access: by Age and Insurance Type (Continued)

Panel B: By Insurance Type

	(1) Private insurance	(2) Medicaid	(3) Medicare	(4) Self-pay
Payday	0.182***	-0.019	0.070	0.409
	(0.058)	(0.114)	(0.095)	(0.924)
Effects of payday access	19.8%	-1.9%	6.9%	50.5%
Observations	12,674	10,685	9,718	2,573
Number of zip codes	1,824	1,535	1,394	369
Controls	X	X	X	X
Border trends	X	X	X	X
County trends	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X
Cluster	county	county	county	county

Table 11: Relationship Between Suicide Attempts (Poisoning) and Payday Access: by Substance Type

This table represents zip-level regressions of suicide attempts on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable of each column is the number of suicide attempts (by poisoning) by patients of the denoted age group and substance type used for suicide attempts. "Effects of payday access" is the exponentiated coefficient of the "payday" variable, which is the percentage change in the expected number of suicide attempts due to access to payday loans. "Average suicide attempts (per 100,000)" is the average rate of suicide attempts in the denoted group. "Additional suicide attempts (per 100,000)" is the percentage change in the expected number of suicide attempts attributable to access to payday loans. To save space, this table omits the coefficients of border trends, county-specific trends, zip code fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). All models report standard errors clustered by county, which are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Psychotropic drugs			Other medicinal drugs			Non-medicinal substances		
	All ages	Aged under 65	Aged 65 and over	All ages	Aged under 65	Aged 65 and over	All ages	Aged under 65	Aged 65 and over
Payday	0.202***	0.198***	0.276	0.127***	0.134***	-0.085	-0.108	-0.104	-0.882
	(0.070)	(0.065)	(0.312)	(0.047)	(0.050)	(0.241)	(0.166)	(0.178)	(1.311)
log(wage)	-0.020	-0.014	-0.165	-0.054	-0.064	0.093	-0.089	-0.035	-1.727
	(0.096)	(0.101)	(0.294)	(0.062)	(0.063)	(0.341)	(0.214)	(0.193)	(1.677)
log(employment)	0.138*	0.161**	-0.160	0.121**	0.120**	0.008	-0.297	-0.257	-0.670
	(0.075)	(0.078)	(0.308)	(0.050)	(0.053)	(0.233)	(0.187)	(0.181)	(1.036)
log(establishment)	0.137	0.094	0.748	0.153	0.126	0.806	0.908**	1.067***	-0.345
	(0.153)	(0.165)	(0.554)	(0.123)	(0.127)	(0.536)	(0.371)	(0.413)	(1.599)
Total number of discharges (per 1,000)	0.000	0.000	-0.000	0.001	0.001	0.000	0.004	0.003	0.010
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.011)
Effects of payday access	22.4%	21.9%	31.8%	13.5%	14.3%	-8.1%	-10.2%	-9.9%	-58.6%
Average suicide attempts (per 100,000)	16.9	18.3	7.8	26.8	29.6	8.6	2.1	2.3	1.2
Additional suicide attempts (per 100,000)	3.8	4.0	2.5	3.6	4.2	-0.7	-0.2	-0.2	-0.7
Observations	12,479	12,444	5,431	13,172	13,102	5,744	7,384	7,118	1,474
Number of zip codes	1,796	1,791	778	1,898	1,888	823	1,058	1,020	211
Controls	X	X	X	X	X	X	X	X	X
Border trends	X	X	X	X	X	X	X	X	X
County trends	X	X	X	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X	X	X	X
Cluster	county	county	county	county	county	county	county	county	county

Table 12: Robustness Tests

This table represents zip-level regressions of suicide risks on the payday access indicator. All regressions report coefficients from Poisson regressions estimated by the Poisson quasi-maximum likelihood estimator (QMLE). The dependent variable is suicide attempts by age group. Panels A and B perform subsample analyses. Panel A restricts the sample by zip code population, and Panel B by the number of non-zero suicide counts of zip codes (out of 7 year-counts). Panel C reports the results from a falsification test, where "FakePayday" equals 1 if a zip code is within 25 miles of a border of states that do not allow payday loans (e.g., Vermont, Massachusetts, and Connecticut) after 1997, and 0 otherwise (See Figure 7). To save space, this table omits the coefficients of controls, border trends, county-specific trends, ZIP fixed effects, and year fixed effects. The data used to produce this table are State Inpatient Data (SID). Standard errors are clustered by county and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Dropping Sparsely Populated Zip Codes

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline sample: all zip codes		Zip codes with pop >= 1k		Zip codes with pop >= 3k	
	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over
Payday	0.109**	0.018	0.095**	-0.021	0.102**	0.023
	(0.042)	(0.177)	(0.041)	(0.162)	(0.040)	(0.164)
Observations	13,563	8,252	12,033	8,064	9,213	7,339
Number of zip codes	1,960	1,183	1,728	1,155	1,321	1,051
Controls	X	X	X	X	X	X
Border trends	X	X	X	X	X	X
County trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 12: Robustness Tests (Continued)

Panel B: Dropping Zip Codes with Too Many Zero Suicide Attempt Counts

	(1)	(2)	(3)	(4)	(5)	(6)
	No zero suicide attempt count		Number non-zero >= 5		Number non-zero >= 2	
	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over	Aged under 65	Aged 65 and over
Payday	0.140***	0.017	0.103**	0.025	0.106**	0.026
	(0.049)	(0.183)	(0.043)	(0.177)	(0.043)	(0.173)
Observations	7,172	6,320	9,914	7,654	12,942	8,186
Number of zip codes	1,028	905	1,422	1,096	1,864	1,173
Controls	X	X	X	X	X	X
Border trends	X	X	X	X	X	X
County trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county

Table 12: Robustness Tests (Continued)

Panel C: Falsification Test: Placebo Border Effects

	(1) All ages	(2) All ages	(3) Aged under 65	(4) Aged under 65	(5) Aged 65 and over	(6) Aged 65 and over
FakePayday	-0.004	-0.004	0.027	0.028	-0.048	-0.045
	(0.032)	(0.033)	(0.037)	(0.037)	(0.075)	(0.074)
log(wage)		0.004		-0.006		0.024
		(0.056)		(0.070)		(0.190)
log(employment)		0.038		0.053		-0.112
		(0.056)		(0.057)		(0.193)
log(establishment)		0.109		0.041		0.489*
		(0.150)		(0.149)		(0.279)
Total number of discharges per 1,000		0		0.000		0.001
		(0.000)		(0.000)		-0.001
Observations	14,063	13,662	13,951	13,563	8,330	8,252
Number of zip codes	2,009	1,976	1,993	1,960	1,190	1,183
Controls		X		X		X
Border trends	X	X	X	X	X	X
County trends	X	X	X	X	X	X
ZIP fixed effects & Year fixed effects	X	X	X	X	X	X
Cluster	county	county	county	county	county	county