Geographic Diversification and Commercial Bank Insolvency Risk and Essays on Crowdfunding and Subscription Games

Andrew Swanson
Clemson University

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Geographic Diversification and Commercial Bank Insolvency Risk and Essays on Crowdfunding and Subscription Games

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the Graduate School of
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of the Requirements for the Degree
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by
Andrew Swanson
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Accepted by:
Dr. Paul Wilson, Committee Chair
Dr. Patrick Warren
Dr. Howard Bodenhorn
Dr. Dan Miller
Abstract

The first chapter of this dissertation is a study into the effects of geographic diversification on insolvency risk for commercial banks in the United States. Using a logit model, this paper finds that, ceteris paribus, more geographically diversified banks exhibited a lower probability of insolvency during both banking crises, with the magnitude of these effects being smaller in the recent banking crisis. Furthermore, allowing for portfolio choices to vary, and holding commercial bank size constant, banks with greater geographic diversification during the crisis of the 1980s and 1990s were overall less likely to become insolvent, while there is no systematic difference in the overall probability of insolvency during the recent crisis.

Using data from the non-equity crowdfunding website Kickstarter.com, the second chapter of this dissertation analyzes the behavior of potential crowdfunders in committing funds to projects in order to increase the probability that said projects will be successfully funded, and thus come into existence. This study finds evidence that while potential funders are aware of, and react to, possibilities for increasing the probability of project success, these effects are economically small. These results suggest that most funders contribute to non-equity crowdfunding projects for either altruistic reasons, or in order to purchase some non-equity reward being offered by the project creator.

The third chapter develops a simple subscription game in order to analyze the ex ante inefficiencies of the voluntary provision of a discrete public good in the presence of incomplete information and a monopoly provider. Symmetric pure strategy Bayesian Nash equilibria are established as solutions to the subscription game. All considerations of the subscription game are ex ante inefficient. Inefficiencies are reduced with increased market size, and greater with increasing public good cost. Inefficiencies increase with the scale of the public good, suggesting that high cost public goods benefiting many individuals may be difficult to provide through a subscription game similar to the one presented in this paper. Inefficiency is also increased when the provider of the public good is a profit
maximizing monopoly, with the relative inefficiencies between a monopoly and benevolent provider remaining consistent across economic conditions considered.
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Finally, I would like to express the deepest gratitude to my family, including those whom are no longer with us today, for their support during times both good and bad. A special debt of gratitude is owed to my mother, Lynn Swanson, whose support throughout my life has never wavered, whatever the circumstances.
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Chapter 1

Geographic Diversification and Ex Post Commercial Bank Insolvency Risk

1.1 Introduction

Geographic diversification in the United States commercial banking industry increased following a period of bank branching deregulation beginning in the 1980s, and ending with passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. While many states allowed for some form of intrastate branching prior to this wave of deregulation, interstate branching was restricted by regulations, severely limiting the ability of commercial banks to effectively diversify geographically.\(^1\) The Riegle-Neal Act permitted full interstate bank branching beginning in 1997, ushering in a long period of commercial bank consolidation in the United States. Due to possible risk-return trade-off choices on the part of commercial banks, it is ambiguous whether greater geographic diversification in the commercial banking industry increases or decreases insolvency risk. The answer to this question is of importance to both regulators and to commercial banks.

The period between the financial crisis of the 1980s and early 1990s, and the most recent financial crisis, was one of extraordinary stability in the commercial banking industry in terms

\(^1\)For a complete history of branching laws in the United States, see Calomiris (2000)
of bank failures. In the 11 years from June 30, 1997 to June 30, 2008 there were a total of 40 commercial bank failures in the U.S.\(^2\) Over this same period of time, the number of commercial banks headquartered in the U.S. fell from 9,228 to 7,123, evidencing the high degree of consolidation in the U.S. since Riegle-Neal was enacted. Employing a logistic regression, this paper makes use of data on banks that failed during the previous and most recent financial crises in order to estimate the ceteris paribus effect of geographic diversification on the insolvency risk faced by commercial banks during both crises, and to compare these effects across crises. To my knowledge this methodology has not been used for estimating the effects of geographic diversification on insolvency risk during either crisis. In fact, no study has attempted to estimate this effect using any methodology for the post-2007 period. I find that increased geographic diversification significantly decreased the probability of failure for commercial banks in both of the crises in question. The reduction in the probability of failure was greater during the previous crisis.

Commercial banks that are able to reduce ceteris paribus insolvency risk through greater geographic diversification may then choose to increase expected revenue streams by engaging in higher return, higher risk investments. This could be done in different ways; banks may decrease their equity-to-asset ratio, increase the amount of high risk loans they make, and invest in riskier non-loan assets such as mutual funds, etc. Therefore, if one finds that, all else equal, greater geographic diversification results in lower insolvency risk, it may still be the case that commercial banks with greater geographic diversification are ultimately more risky due to engaging in riskier behavior along other dimensions. This paper provides evidence that geographically diverse banks did not hold riskier portfolios in the prior crisis, but did in the most recent crisis, namely through lowering their equity-to-asset ratio and becoming more highly leveraged.

1.2 Economic Theory and Previous Empirical Results

A bank fails, i.e., becomes insolvent if one of two events occurs; either the bank is unable to meet present financial obligations or the Federal Deposit Insurance Corporation (FDIC) puts the bank under receivership and begins the process of winding down the bank, or finding a partner for a forced merger. Since the FDIC Improvement Act of 1991, the FDIC begins the process of winding down a commercial bank when the tangible equity ratio, equal to equity less intangible assets such as

\(^2\)Statistics from the FDIC failed bank list.
goodwill and preferred stock, divided by total assets, falls below .02. A bank’s equity level provides a buffer between different potential shocks that a bank may be subject to, and insolvency.³

Since at any given time commercial banks have incomplete control over equity levels, any particular shock to equity of sufficient magnitude, or a series of shocks to equity of sufficient cumulative magnitude, can lead to insolvency. These shocks can come from three main sources: shocks to asset values, liquidity shocks, and shocks to current revenue or cost streams. Shocks to asset values occur due to decreased market prices and decreased expected revenue streams from said assets. Shocks to liquidity generally occur if demand deposits are unexpectedly withdrawn from branch offices, leaving the bank with less cash and other liquid assets to meet short-term obligations. In order to meet short-term obligations a commercial bank may subsequently be forced to sell traditionally illiquid assets at lower than market values or to acquire liquid assets, such as short-term interbank loans, often at prices significantly higher than demand deposit prices. Shocks to revenue and cost streams occur if assets suddenly stop producing revenue, such as loans becoming past due, or if operating costs increase for unexpected reasons, whether this be the liability access issues presented above or unexpected litigation costs, etc. Note that shocks to revenue streams may lead to subsequent asset value shocks insofar as they translate into lower expected future revenue streams from assets and require the commercial bank to write down the values of these assets.

Markowitz (1952) first investigated the benefits of portfolio diversification and many researchers have since added to the literature on portfolio theory. Geographic diversification, in particular, may decrease insolvency risk by reducing the variance of the underlying distributions for asset value shocks, liquidity shocks, and revenue or cost stream shocks. If local economic conditions play a role in driving the various shocks to which commercial banks are exposed, and local economic conditions are less than perfectly correlated, then geographic diversification may reduce the overall variance of these shocks. Researchers arguing for the deregulation of commercial bank branching in the 1980s made similar arguments (e.g. Department of Treasury (1981), Calomiris et al. (1987), and Wheelock (1992)). Note that, as Levonian (1994) points out, this reduction in overall variance may not be true for any one bank choosing to expand into a new geographic market if the new market has a higher shock variance than markets in which the bank already operates.

³Ultimately, it is a measure of the amount by which a bank’s assets can decline before their liabilities exceed those assets.
versification may choose to increase expected revenue streams by engaging in higher return-higher risk investments, within the bounds allowed by regulators. This could be done in different ways; banks may decrease their equity-to-asset ratio, increase the amount of high risk loans they make, and invest in riskier non-loan assets such as mutual funds, etc. In terms of insolvency risk this could be modeled as Figure 1. Curve I represents a bank with a ceteris paribus lower geographic diversity level while curve II represents a bank with a higher level of geographic diversification. A commercial bank, if operating efficiently, will choose a point on its respective risk-return curve based upon that bank’s risk preference.

The following example will help illustrate the concept. A risk-averse bank, or a bank being constrained in its actions by regulation, may choose point A on curve I. If this bank similarly becomes more geographically diversified, and is now operating on curve II, while they will enjoy higher returns, may choose a point in which overall risk is decreased, such as (B), or a point in which overall risk is increased, such as (C). This choice will be determined by that bank’s risk preference expansion. Whether a bank chooses to increase or decrease ex ante insolvency risk is dependent on the risk preference for that bank. The question of overall changes in insolvency risk due to increased geographic diversification is thus empirical in nature.

The financial crisis of the 1980s and early 1990s led to a series of empirical studies seeking to determine the affect of geographic diversification on the insolvency risk of bank holding companies (BHCs) over the time period of the crisis. A consensus exists in terms of the effect that geographic diversification has on insolvency risk, holding certain portfolio composition measures constant. Of the five studies estimating this ceteris paribus effect, three find unambiguous and significant decreases in insolvency risk due to geographic diversification (Liang and Rhoades (1988), Rivard and Thomas (1997), and Demsetz and Strahan (1997)). Of the two remaining studies, Rose (1996) finds a decrease in insolvency risk for already diverse banks, while Emmons et al. (2004) finds a decrease in insolvency risk for urban commercial banks with assets in a single county. These studies use differing methodologies, measures of risk, unit of observation, and time frame. These differences and the results for all empirical studies cited in this paper are presented as Table 1 for the readers convenience.

A similar consensus is not present in the studies that estimate whether more geographically diverse BHCs have higher overall insolvency risk. Liang and Rhoades (1988) find a decrease in overall insolvency risk for more geographically diverse banks. On the other hand, Chong (1991) and Hughes
et al. (1996) find an increase in overall insolvency risk. Lastly, Akhigbe and Whyte (2003) find no significant effect for banks with assets in one state, and a significant decrease in insolvency risk for banks with assets in multiple states. It is difficult to pinpoint the cause of this disagreement, as the methodologies and time frames used by the studies differ. Again, these studies are summarized in Table 1.

Technologies developed within the commercial banking industry give reason to believe the importance that geographic diversification has on commercial bank insolvency risk may have changed since the financial crisis of the 1980s. While Berger and DeYoung (2006) show that technological progress has decreased the costs of geographic expansion as well as increase the ability of commercial banks to exert central control over, and export efficiencies to, bank branches, recent technological progress may have also decreased the need for geographic diversification. Increased securitization of loans as well as online loan origination may have decreased the importance of physical branch diversification for the purpose of diversifying geographic risk associated with asset values. Furthermore, the ability to manage deposit accounts online may have decreased the importance of physical branch diversification for the purpose of diversifying risk associated with demand deposit accounts. On March 30, 2003, approximately 46 percent of commercial banks in the U.S. had a website that allowed for the electronic managing of deposit accounts while on June 30, 2008, that same statistic is approximately 84 percent.\footnote{Statistics from the FDIC quarterly call reports, item RCFD4088.} In particular, geographic diversification may have become less important as a determinant of insolvency risk during the recent banking crisis as opposed to the prior crisis.

Using data on BHCs from the time period between the previous and most recent crisis, Deng and Elyasiani (2008) and Goetz et al. (2014) find that, holding portfolio characteristics constant, the significant and negative effect of geographic diversification on insolvency risk persists beyond the previous financial crisis. Furthermore, while neither of the two studies mentioned above include data post-2007, Aubuchon and Wheelock (2010) find evidence that state market conditions are correlated with commercial bank failure in the most recent crisis, leading to an unbalanced level of failures across the United States. The above evidence suggests that geographic diversification is still an important factor determining risk of insolvency.

Three studies estimate whether more geographically diverse banks exhibit higher overall insolvency risk using data from the time period between the two crises. Deng et al. (2007) and Goetz et al. (2014) find that geographically more diverse BHCs exhibit less overall insolvency risk.
in the time period after the previous crisis. Dick (2006) finds that commercial banks, after the enactment of Riegle-Neal in 1994, choose to engage in greater portfolio risk. These studies suggest that consolidation during the time period between the previous and most recent crisis results in banks with less insolvency risk, even though banks choose riskier portfolios after consolidation.

The majority of the empirical literature presented above focuses on estimating the effect of geographic diversification on insolvency risk using either market assessed risk measures, or alternatively, measures based on the volatility of earnings. These studies identify ex ante risk levels conditional on geographic diversity levels. This study proposes to investigate the contribution of geographic diversification, or lack thereof, in determining which banks failed during the two most recent financial crises. In doing so, it is possible to compare these effects across both crises. Carlson (2004) is the only study, of which I am aware, to use data on actual bank failures in estimating the contribution of geographic diversification to bank insolvency, and Carlson is focused on bank failures during the Great Depression. Carlson (2004) finds that branch banks were more likely to fail relative to unit banks during the Great Depression, presenting a possible explanation for these results based upon increased competition, due to branching, creating banks existing on the margin who chose to wind down.\(^5\) This study adds to the literature on the effects of geographic diversification on the probability of bank failures across the two banking crises of the past half-century.

1.3 Empirical Methodology and Data

1.3.1 Methodology

For the main results of this paper a bank will be assumed to fail if capital adequacy (\(capad\)), dips below a minimum level \(capad_{\text{min}}\), where \(capad\) is defined as the ratio of equity minus goodwill to assets\(^6\), or the FDIC puts the bank under receivership. The value \(capad_{\text{min}}\) is chosen to be 0.02 due to the previously mentioned FDIC Improvement Act of 1991. Define the binary variable \(\text{failure}_{i,t}\) as

\[
\text{failure}_{i,t} = \begin{cases} 
1 & \text{if } capad_{i,t} \leq 0.02 \\
0 & \text{if } capad_{i,t} > 0.02
\end{cases}
\]  

\(^5\)A unit bank is one with a single branch, while a branch bank has multiple branches.

\(^6\)This definition of capital adequacy is taken from Wheelock and Wilson (2000)
where \( i \) indexes bank, and \( t \) denotes year \( t \). Furthermore, \( \text{failure}_{i,t} = 1 \) if the commercial bank is included in the FDIC failed bank list. Given the definition of \( \text{failure} \), we can model the probability of commercial bank failure using the logit distribution. Then the probability of failure can be parameterized as

\[
P(\text{failure}_{i,t} = 1|X_{i,t}, Z_{i,t}) = \frac{e^{\beta X_{i,t} + \alpha Z_{i,t}}}{1 + e^{\beta X_{i,t} + \alpha Z_{i,t}}},
\]

where \( X_{i,t} \) is a vector of covariates representing a commercial bank’s capital adequacy level, balance sheet composition, liquidity level, current earnings, and geographic diversity, while \( Z_{i,t} \) is a vector of controls. Due to the nature of the available data, \( \text{capad} \) cannot be observed continuously over time. What is observed is whether a bank fell below a \( \text{capad} \) level of 0.02 during a particular time period, leading to the above specification being considered as an application of a latent variable model. This methodology for identifying probability of failure does not identify historic or future \textit{ex ante} risk levels for different asset classes and portfolio positions, but it does allow for identification of shocks, and thus to commercial bank characteristics that led to failure in the prior and most recent financial crises.

While this study does not attempt to formally model commercial banks’ decisions regarding the mix of reduced risk due to geographic diversity and increased revenue, it is possible to present evidence on whether geographically more diverse banks were \textit{overall} more susceptible to shocks than geographically less diverse banks. After controlling for the ceteris paribus effect of geographic diversity it is possible to estimate fitted failure probabilities for different diversity levels. While this would not be proof of causality if geographically more diverse commercial banks are overall more or less risky, it would provide evidence of a link between diversity and decisions to engage in some form of riskier behavior, whatever the mechanism.

### 1.3.2 Data

As noted above, commercial bank failure for the main regressions presented in this paper is technically defined as any commercial bank that was officially wound down by the FDIC, including banks that were subsequently acquired by another bank in part or as a whole, as well as any bank whose reported capital adequacy ratio dropped to less than 0.02 during the relevant time period. For example, a commercial bank reporting an equity-to-asset ratio at or below 0.02 on the June 30, 1986 call report would be categorized as failing sometime between April 1, 1986 and June 30,
Data on commercial banks being wound down under FDIC receivership are obtained from the FDIC. Levels of equity-to-assets ratios are explained later in the paper.

For the time period 1985–1992 Delaware and Hawaii suffered no commercial bank failures while many states only experienced 1–3 commercial bank failures. Texas was an epicenter for commercial bank failures as there were 610 failures in that state alone, while neighboring states all had disproportionate numbers of bank failures. A heat map displaying this concentration in the number of failures by state is presented as Map 2a of Figure 2. In all, there were 1501 commercial bank failures representing approximately $350 billion constant 2009 dollars in assets during the period 1985–1992. For the time period 2008–2013 the states with the largest numbers of failures are more spread out geographically, providing some evidence that the economic shocks leading to the financial crisis were more nationwide phenomena, even if commercial banks failed in localities suffering some form of local shock. A heat map of commercial bank failures by state is presented as Map 2b of Figure 2. There are three main regions for commercial bank failures in the most recent crisis: the Southeast region centered around Georgia and Florida, the Midwest region centered around Illinois, and the West region centered around California. Many states had no commercial bank failures during the most recent crisis. In all there were 417 commercial bank failures representing approximately $382 billion constant 2009 dollars in assets during the period 2008–2013.

The geographic diversity measure used in this study is constructed from the FDIC’s Summary of Deposits data. These data include all FDIC insured commercial banks in the United States and reflect deposits as of June 30th for each year, for each bank. The measure of diversity is defined as

\[ \text{diverse}_i = 1 - \sum_{c=1}^{C} \left( \frac{\text{deposits}_{c,i}}{\text{totaldeposits}_i} \right)^2, \tag{1.3} \]

where \( i \) denotes bank and \( c \) denotes a particular county, which serves as the market in this risk measure. A commercial bank will have a value of zero for \( \text{diverse} \) if all of the bank's deposits are concentrated in a single county. This measure has been used in previous studies such as Hughes et al. (1999), Deng et al. (2007), and Goetz (2012).

Summary statistics for the diversity measures for periods 1985–1992 and 2008–2013 are presented in the first row of Table 2. Commercial banks are more geographically diverse on average for the 2008–2012 sample compared to the 1985–1992 sample. Many commercial banks in both sample time periods only take deposits in one county. In fact, 91 percent of banks have a \( \text{diverse} \)
value of zero on June 30, 1985, while 50 percent of banks have a diverse value of zero on June 30, 2008. While diversity has greatly increased in the interim between the prior and most recent financial crises, there are still a large number of commercial banks operating in only one county.

1.3.2.1 Asset Exposure Measures

Data for commercial bank asset and equity levels are collected from the FDIC’s Quarterly Call Reports of Condition and Income. These call reports are mandatory documentation required of all commercial banks operating within the United States. Data are collected from the June call reports for the years 1985–1992 and 2008–2013 for all commercial banks in the United States, regardless of size. Commercial banks headquartered outside of the U.S. are excluded from the data set. Assets from the balance sheet have been separated into four main categories; cash and balances due from depository institutions (cash), securities (sec), loans, and other assets. Loans and other assets are further broken down into more granular categories. Other assets are broken out into other real estate owned by the commercial bank (otherreal) and all other various assets (otherasset). All asset category levels are transformed into ratios by dividing through total assets of the commercial bank, thus giving them an interpretation of exposure levels to particular asset categories.

Loans are further broken down into the following categories: (1) farm measures loans secured by farmland as well as loans made to farmers, whether these loans are made to finance agricultural production or otherwise; (2) resreal measures loans secured by 1–4 family residential properties; (3) comhouse measures loans secured by residential properties meant for 5 or more families. Ideally resreal would only include loans secured by single family residential properties while comhouse would include loans secured by any multifamily residential properties, but these data are unavailable in the call reports\(^7\); The (4) dev measures loans secured by construction, land development, and other land loans; (5) comreal measures loans secured by nonfarm, nonresidential properties; (6) comloan measures commercial and industrial loans; (7) otherloan measures all other loans held by the commercial bank including loans to depository institutions, loans for expenditure purposes, and loans made to governments both foreign and domestic. Again, these loan category levels are transformed into ratios by dividing through total assets of the commercial bank, thus giving them an interpretation of exposure levels to particular loan categories.

\(^7\)It would be best to measure real estate loans for commercial and non-commercial purposes as there is an expectation that these two types of loans may have differential shocks associated with them.
1.3.2.2 Current Earnings and Liquidity Measures

The variable $earn$ measures the ratio of income after taxes to assets of the commercial bank. Data on income are collected from the quarterly call reports. Income is a flow variable, and as such, data on income are collected for each year interval starting on July 1st and ending June 30th of the following year. If a commercial bank fails during the interval, then $earn$ measures earnings up to the most recent available information.

The variable $liq$ measures the liquidity of the commercial bank. The vast majority of short-term obligations on the part of the bank are in the form of demand deposits. A commercial bank may also have short term liabilities or assets in the form of activity in the federal funds market. Thus, the variable $liq$ is equal to the ratio of cash plus net federal funds sold to demand deposits.

Control variables include $hold$, $age$ and $size$. The variable $hold$ is a dummy variable equal to one if the commercial bank is a part of a multi-bank holding company and equal to zero otherwise, $age$ is equal to the number of years that the commercial bank has been chartered, and $size$ is equal to the log of total assets of the commercial bank in real terms.

1.3.2.3 Summary Statistics, Non-Diversity Independent Variables

Summary statistics for the above variables are presented as Table 2. There are a number of striking differences between the two samples. $Capad$ levels are close to two percentage points higher on average in the later sample, leading to the potential conclusion that as a whole, commercial banks were less risky, as measured by leverage, in the latter period. Note however, that many of the traditionally more risky loan categories take up a larger share of total assets in the latter period. These riskier categories include $comhouse$, $comreal$ and $dev$. Increases in the riskier asset classes during the financial crisis come mostly at the expense of $sec$, $otherloan$, and $otherasset$. So while commercial banks in the financial crisis have higher $capad$ levels on average, they are also more exposed to classically risky asset classes as well. In fact, loans make up about 62 percent of total commercial bank assets on average in the time period 2008–2013, while the same statistic is about 52 percent in the period 1985–1992.
1.4 Results

Pooled logit regressions are run separately for the first banking crisis and most recent crisis, corresponding to the time periods of 1985–1992 and 2008–2013 respectively. Due to the fact that, by definition, the asset exposure variables sum to one it is necessary to exclude a category for estimation purposes. The asset exposure variable excluded in this study is *cash*. The choice of *cash* was made for ease of inference as *cash* is theoretically a relatively safe asset exposure category. Effects of increasing asset exposure levels for a particular asset classification are thus interpreted as relative to *cash*. Furthermore, the ceteris paribus marginal effects for variables constructed with bank assets as the denominator are due to changes in the numerator, holding the denominator, or total bank assets, constant. Finally, these variables are scaled such that marginal effects reported measure a percentage point change in probability of insolvency for a one percentage point increase in the variable. Variables that are constructed with total bank assets as the denominator include *capad* and all of the asset exposure variables. Year fixed effects are included in both regressions. Coefficients from the logit regression are reported as well as average marginal effects (AMEs) and 95% confidence levels for the AMEs. These regression results are reported in Table 3.

1.4.1 Results for *capad* and *earn*

The effects of *capad* and *earn* on the probability of insolvency have been found to be negative and significant in all previous studies. This should be no surprise as *capad* is the buffer between losses and insolvency for the commercial bank while *earn* directly decreases equity if a commercial bank suffers losses in a quarter. As other studies have found, increases in *capad* and *earn* are found to decrease the probability of insolvency during both crises. While the AMEs of both of these variables are smaller in magnitude during the most recent crisis, the AMEs are still large in absolute terms. On average, during the first banking crisis, an increase in *capad* of 0.01 resulted in a decrease to the probability of insolvency of 0.60 percentage points. The same effect for the most recent crisis is a decrease in probability of 0.55 percentage points. An increase in income of 1 percent of total assets led to a decrease in the probability of insolvency of 0.37 percentage points during the first crisis and a decrease in the probability of insolvency of 0.23 percent during the most recent crisis.
1.4.2 Results for Asset Exposure Levels

There are marked differences between the two crises with respect to the effects that different asset exposure levels have on the probability of insolvency. In the first crisis, all asset exposure classifications have significantly different AMEs from cash at the 5 percent confidence level. The only classification that has a negative AME on the probability of insolvency during either crisis is sec in the first crisis. All other asset classifications have a positive AME on the probability of insolvency during the first crisis, with otherreal having the largest effect. A 0.01 unit increase in otherreal increased the probability of insolvency by 0.20 percentage points. While there are differences in the AMEs of exposure to various loan categories in the first crisis, most notably that resreal has a magnitude of effect multiples smaller than other categories, it is the case that holding loans of any category as opposed to cash led to higher levels of insolvency risk. During the most recent crisis this was not the case, as the only loan categories significantly different from cash are comhouse and dev. In the most recent crisis, and similar to the first crisis, otherreal has the largest positive AME of all asset classifications on probability of insolvency, with a 0.01 unit increase in otherreal increasing the probability of insolvency by 0.11 percentage points on average.

1.4.3 Results for size and hold

As many other studies have previously found, an increase in bank size measured by total bank assets is related to a lower probability of insolvency during the first crisis, after controlling for the makeup of a commercial bank’s asset portfolio. In the most recent crisis, however, bank size is unrelated to insolvency probability after controlling for a commercial bank’s asset portfolio. There will be more on this result later in the paper. The creation of multi-bank BHCs is understood to have been an effective way for commercial banks to access diverse markets before branching deregulation, and, in line with this reasoning, the effect of belonging to one of these BHCs decreased the probability of insolvency during the first crisis. Surprisingly, the negative effect of belonging to a multi-bank BHC on the probability of insolvency persists, albeit of less magnitude, during the most recent crisis, even though most barriers to expansion have been removed.
1.4.4 Results for \textit{diverse}

The variable \textit{diverse} measuring geographic diversification has the correct sign and is significant at the 5 percent confidence level for both crises. It can be difficult to interpret unit changes in a variable such as \textit{diverse}, and so it may be beneficial to think of a standard deviation change in \textit{diverse}. For example, during the first crisis the \textbf{approximate} average decrease in the probability of insolvency from a one standard deviation increase in \textit{diverse} is equal to -0.20 percentage points, while the same effect is equal to -0.11 in the most recent crisis. At first glance these effects may seem economically small.

Simply finding the overall mean of the marginal effects hides interesting information about how these marginal effects differ across banks. A graph of the means of the marginal effect of geographic diversification for different groupings of \textit{diverse} levels for both time periods is presented as Graph 3b of Figure 3. Note that there are systematic differences in the AMEs for different levels of \textit{diverse} during the first crisis. The AMEs are most negative at lower levels of the variable \textit{diverse}, suggesting that there were “low hanging fruit” in terms of future geographic diversification for commercial banks with already low geographic diversity. There seems to be no systematic pattern for the marginal effects on \textit{diverse} during the most recent crisis.

The difference in systematic patterns of marginal effects between the prior and most recent crisis may be due to the fact that during the prior crisis commercial banks were constrained in their branching activities by regulatory legislation. These constraints left many commercial banks unable to capitalize on opportunities to lower insolvency risk through geographic diversification. Graphs 3a and 3c of Figure 3 display histograms of \textit{diverse} levels across banks for the 1985–1992 and 2008–2013 time periods, respectively. Commercial banks with a \textit{diverse} level lower than 0.1 make up a much smaller proportion of banks for the time period 2008–2013. The reduction in the proportion of banks with \textit{diverse} levels less than 0.1 has been approximately distributed evenly across the rest of the distribution of commercial banks. Taken together, this is evidence that banks with the most extreme marginal effects for reducing insolvency risk through geographic diversification have indeed become more diversified.
1.4.5 Overall Failure Probabilities for Commercial Banks by Diversity Levels

As stated earlier, high levels of geographic diversity measures may be correlated with certain asset class exposure and capital levels. Insofar as there are positive correlations between geographic diversity and the variables that the logit model deemed risky during either crisis, then a commercial bank that is more geographically diverse may in fact have been exposed to more/stronger shocks during either crisis. So, even though, ceteris paribus, higher levels of geographic diversification led to lower insolvency risk in both crises, it may be the case that more geographically diversified banks are overall more likely to fail in either crisis. Correlations between the diversity measure and asset classification measures as well as \( capad \) are presented as columns 2 and 5 of Table 4. Note that the correlations generally lead to the conclusion that a more geographically diverse bank is also more likely to be exposed to asset classifications that are \( ex \ post \) more risky in both crises.

Since the size of a commercial bank and its geographic diversification are highly correlated, it may be important to control for the tendency that large banks have a risky portfolio when investigating if geographically diverse banks tend towards a relatively risky portfolio. In order to separate these correlations I run a series of OLS regressions of the form

\[
y_{i,t}^* = \beta_0 + \beta_1 \cdot \text{diverse}_{i,t} + \beta_2 \cdot \text{size}_{i,t} + \epsilon_{i,t},
\]

where \( y^* \) corresponds to each of the asset exposure classifications and \( capad \). Results of these regressions are reported as columns 3–4 and 6–7 of Table 4. Many of the coefficients on \( \text{diverse} \) from these regressions reverse the sign compared to the correlation estimates. After controlling for size, higher geographic diversity is correlated with greater exposure to \( \text{farm} \) and \( \text{resreal} \) in both samples. After controlling for size, higher geographic diversity is correlated with less exposure to \( \text{comhouse}, \text{comreal}, \text{comloan} \) and \( \text{foreign} \) in both samples. In other words, banks that have a physical presence in many local markets hold more “localized” loans on their balance sheet on average. Larger banks hold more business and commercial type loans on their balance sheets. The most important difference between the two crises is the estimate for \( \beta_1 \) in the OLS regression on \( capad \). In the first period higher levels of \( \text{diverse} \) are unrelated to \( capad \) levels, while in the most recent crisis higher levels of \( \text{diverse} \) are related to lower levels of \( capad \).

As the above analysis shows, it is important to hold size constant in attempting to ascertain
if more geographically diverse commercial banks held riskier portfolios in either of the financial crises. As such, fitted values for the probability of insolvency are calculated for each bank, in each time period, holding size constant at the mean size of the relevant period. Fitted values are constructed using the results of the logit model estimated earlier in the study. These fitted values are then averaged over different levels of diverse and presented in Table 5. For the first crisis there is a clear drop in the fitted probability of failure between commercial banks which had all of their deposits in one branch and those banks which had even a slight increase in the geographic dispersion of their deposits across markets. There is no systematic difference in the probability of insolvency across diverse levels after the initial decrease in risk of insolvency. There seems to be no pattern in the fitted probabilities of insolvency risk for the most recent crisis.

Taken together, these results suggest a few things. Commercial banks operating one branch in the first crisis were not more capitalized than their highly diversified counterparts, leaving them more vulnerable to exogenous shocks. This could be due to the fact that regulations prevented certain bank managers from reducing risk through geographic diversification, thus leading them to choose a more risky position on the risk-return frontier than they otherwise would. After branch banking deregulation, and the period of consolidation that ensued, a pattern emerges in which more geographically diversified banks are more highly leveraged, thus in some sense spending their risk reduction gains on higher returns. While there are still banks that chose to operate in a single market during the most recent crisis, these banks are highly capitalized banks making more localized loans, such as farming and residential real estate loans.

1.5 Conclusions

Commercial banks in the United States with higher levels of geographic diversification had lower ex post probabilities of insolvency, all else equal, during both the financial crisis of the 1980s and early 1990s and the most recent financial crisis. The marginal effects on insolvency probability are larger for the first crisis as opposed to the most recent crisis, possibly due to legislatively constrained banks operating in one or a few markets. These large marginal effects present in the earlier crisis disappeared over the course of the 1990s and 2000s, possibly due to changes in technology and possibly due to further geographic diversification. The overall probability of insolvency was lower for more geographically diverse commercial banks during the first crisis, with most of this difference
coming from commercial banks that operated in one market. During the most recent crisis there is no clear difference in the overall probability of insolvency across banks with differing levels of geographic diversity. This suggests that, after shifting the risk-reward frontier outwards with geographic expansion, commercial banks chose a similarly risky position on this frontier as before the expansion.
Chapter 2

Paying for Success: An Analysis into Crowdfunder Payments Towards Project Success

2.1 Introduction

Non-equity crowdfunding is the process of tapping into large communities of potential funders to financially support a creative project or idea that generally offers some non-monetary reward in return. This relatively new phenomena has been growing in economic activity since its inception in the late 2000s. While still a small industry, crowdfunding has the potential to grow much larger as a unique marketplace offering a previously unavailable service. Much of the existing literature analyzing non-equity crowdfunding has focused on how these platforms resemble pre-order mechanisms or fund drives. In the first instance a funder may acquire a copy of the output of the creative project; in the latter instance, a funder may gain utility from having donated towards a good cause. Focusing on these two aspects of non-equity crowdfunding may lead to disregarding the potentially important fact individuals may be willing to fund a crowdfunding initiative to see the project succeed. From the perspective of some potential crowdfunders, there is utility to be gained from the success of a crowdfunding initiative, whether from a reward or altruism. These crowdfunders will be willing to pay to realize this utility.
Thought of in this way, non-equity crowdfunding platforms take on the appearance of mechanisms for the voluntary provision of a public good. The mechanism employed by many crowdfunding platforms mimics closely a set of subscription type provision point mechanisms for the private provision of public goods favored by some studies (Admati and Perry (1991), Bagnoli and Lipman (1989), Rondeau et al. (1999) among others.). However, crowdfunding differs importantly from these mechanisms in that they usually offer some private reward or experiential benefit for funders. If crowdfunding platforms are paying towards the successful funding of a project, rather than simply purchasing a reward or experience, then a mechanism like Kickstarter may allow for the creation of goods and services that would otherwise not exist. Understanding the behaviors and motivations of individuals that contribute towards crowdfunded projects is thus important in understanding the potential for value creation in this new marketplace.

This study is an analysis into the behavior of crowdfunders, investigating motives of paying towards the successful funding of creative projects. In particular, this funding may be done separately from purchasing rewards or gaining utility through altruism. Using data from Kickstarter.com, currently the largest non-equity crowdfunding website in existence, I find that while there is evidence for crowdfunders paying towards the successful completion of projects, these types of payments are relatively small, suggesting that funders are motivated by the purchasing of rewards and altruistic giving. This paper adds to the growing literature on the behavior and motivations of crowdfunders. The rest of the paper is organized as follows; section 2 presents an overview of Kickstarter and the motivations of funders within that fund-raising platform, section 3 develops theory underpinning potential funder behavior, section 4 explains the empirical strategy and the data available, and section 5 reports results while section 6 contains a short conclusion.

2.2 Kickstarter

2.2.1 What is Kickstarter?

Kickstarter is a non-equity crowdfunding platform launched in April, 2009, and as of November, 2015, over 9.5 million individuals have pledged funds to different crowdfunding projects. These pledged funds amount to over 2 billion dollars. Kickstarter bans charity fundraising as well as any offers of financial incentives for funding, including equity. Crowdfunding projects on Kickstarter are intended to be “creative”; something created to share with others, in the words of Kickstarter. Each
project has a fund-raising duration period, up to a maximum of 60 days, in which to raise funds towards the creation of some project. If the total amount of pledges meets or exceeds a funding goal set by the creator, then pledges change hands and the project moves forward towards fruition. If the funding goal is not met by the end of the fund-raising duration, no funds change hands and the funding request is unsuccessful. For any successfully funded project, Kickstarter keeps 5% of all funds changing hands.

2.2.2 Project Creator Decisions

There are a multitude of possible benefits for raising funds on a crowdfunding platform such as Kickstarter. Crowdfunding is a potentially inexpensive means for engaging in market demand revelation and advertising through the popularity of the platform itself, creating a situation in which the initial stages of some endeavor can be undertaken at low capital costs. (Agrawal et al. (2013)). Offering rewards that are differentiated from post-funding output, such as early access, or an ability to be involved in the creation process, may allow for a certain level of price discrimination on the part of the project creator as they target high value consumers. Crowdfunding platforms also help solve geographic problems inherent in the agglomeration of angel investors and other forms of traditional seed investment. Agrawal et al. (2011) shows that crowdfunding eliminates many issues in connecting investors and project creators across space.

If a project creator decides to raise funds through Kickstarter, the creation of the project page is the first public announcement of the call for contributions. The creator at this point must make decisions on how much to ask for, the fund-raising duration, what rewards they will offer for different individual contribution levels, and the contents of the project page. While projects with greater funding goals are less likely to be successfully funded, asking for too little can also send a signal of poor project quality. Fund-raising periods can be any length up to 60 days, with Kuppuswamy and Bayus (2015) finding that projects with shorter duration periods are more likely to be successfully funded. Mollick and Nanda (2015) and Ahlers et al. (2015) find that the initial projection of project quality through videos, images, and explanations of the project including a strategy for eventual realization, are an important indicator of ultimate success. The rewards offered by different projects are diverse, from a copy of the artistic output, to executive producer credits, and simple thank you postcards. Each reward has a posted price, or individual funding level necessary to be able to receive said reward. Since this paper is concerned with funder behavior there is no
attempt to model the decisions made by project creators, however, these decisions play a potentially important part in shaping funder behavior. To quickly recap, projects with less ambitious goals, shorter durations, and more extensive initial project pages are more likely to be successfully funded.

### 2.2.3 Three Sources of Utility for Potential Funders

Once a project page is running on the Kickstarter website it can be accessed by potential funders. The decision to fund a particular project, and how much to fund, will be motivated by three basic sources of utility for potential funders. The first, and probably most obvious source, is from the purchase of rewards offered by the project creator for reaching individual funding levels. These rewards are considered to be akin to the purchase of any common good in the economy. While these rewards are considered as common goods in this analysis, oftentimes they are unique and unavailable outside of contributing funds to a project. As already stated, the rewards are incredibly diverse across projects, and so individual tastes over these rewards is assumed to vary across individuals. Utility from the purchase of rewards is only gained upon full funding of the project, because otherwise no funds or rewards change hands. Utility gained from the purchase of rewards is hereafter referred to as reward utility.

The second source of utility comes from what may be considered an altruistic motive, or as Andreoni (1990) puts it, utility gained from a “warm glow” of giving. In the case of crowdfunding, this altruistic utility has been called community benefits, and benefits gained from community participation (Agrawal et al. (2013) and Belleflamme et al. (2014)). These benefits are defined as feeling a part of a group that accomplishes a goal, being involved in the creative process in some small manner, and helping to provide a good for which others might gain (Schwienbacher and Larralde (2010)). A survey presented in Gerber et al. (2012) identifies supporting a creator and engaging in an open community as important motivations for funding projects. Altruistic utility may also be considered the motivation for contributions by friends and family. I assume that the utility gained from an altruistic motive is assumed to depend on the individual funding level in a continuous fashion, rather than the possibility of a discrete utility gain from some set amount of funding. It is further assumed that altruistic utility is only gained upon successful funding of the project, when funds actually change hands.

The final source of utility encompasses all that gained from the successful completion of a project that is not due to rewards or altruism. An example of this might be utility gained from
the completion of a project funding a season of a radio show. Many individuals may gain utility from the completion of this type of project apart from rewards received and any altruism involved. Obviously, this type of utility is also only acquired if the project is successfully funded. As with reward utility and altruistic utility, utility gained from the completion of a project is assumed to vary across potential funders for each project. This type of utility will hereafter be known as project utility.

2.3 Utility Function and Decision-Making for Potential Funders

Most projects offer more than one reward which can be purchased by funders, although only one reward can be chosen by any given funder. To simplify the model for the main section of this paper, it is assumed there is only one reward for any given project. Further simplification is attained by considering that potential funders have either positive altruism utility or reward utility, hereafter known as altruistic or reward types respectively.

2.3.1 Expected Utility for Altruistic Type Funders

For any given project, expected utility for an altruistic type is modeled as

\[ E[U_{i,t} | I_t, \beta_i, \alpha_i(x_{i,t}), x_{i,t}] = \Pr(X_{-i} + x_i \geq G | I_t, x_{i,t}) \cdot (\beta_i + \alpha_i(x_{i,t}) - x_{i,t}), \]  

(2.1)

where \( I_t \) is the information set available to potential funder \( i \) at time \( t \), \( X_{-i} \) is total funding by all other potential funders at the end of the project duration, \( x_{i,t} \) is potential funder \( i \)'s funding level at time \( t \), and \( G \) is the goal level of the project. \( \Pr(X_{-i} + x_i \geq G | I_t, x_{i,t}) \) is the subjective probability that total funding levels exceed the goal by the end of the fund-raising duration conditional on the funding level of, and information set available to, funder \( i \). \( \beta_i \) and \( \alpha_i(x_{i,t}) \) are project and altruism utility respectively.
It is assumed that
\[ \alpha_i(0) = 0 \]
\[ \alpha_i(x_i) \geq 0, \]
\[ \alpha'_i(x_i) \geq 0, \]
\[ \alpha''_i(x_i) \leq 0. \]

Further, it is assumed that the marginal utility of income is constant and equal to one, utility for potential funders conditional on the project being unsuccessful is normalized to zero, and potential funders are not budget constrained for any desired level of funding.

The above utility function states that altruistic types have some positive utility over the successful funding of a project, potentially based upon their individual funding level. Upon successful funding of a project each potential funder will receive project utility \( \beta_i \), no matter their individual funding level, and altruistic utility \( \alpha_i(x_{i,t}) \), which depends on the individual level of funding for altruistic type funder \( i \). It is assumed that an altruistic type can have \( \alpha_i(x_{i,t}) = 0 \ \forall \ x_{i,t} \), resulting in the altruistic type encompassing individuals who only have positive project utility. While, in the above specification, the probability that a particular project will be successfully funded is a function of the individual funding level at time \( t \), or \( x_{i,t} \), I will be analyzing the decision-making of altruistic type funders on the assumption that \( x_{i,t} \) affects this probability, as well as the assumption that \( x_{i,t} \) has no effect on probability of successful funding. This is done to determine easily what behavior is expected if individuals are paying towards a project success.

2.3.1.1 Decision-making by Altruistic Type Funders, Assumed to have No Effect on Probability of Success

If an altruistic type funder has no effect on the probability of success, or subjectively believes they have no effect on the probability of success, then expected utility is given as Equation 2.1 with the probability term independent of \( x_{i,t} \). An altruistic type funder will then fund a first dollar if\(^1\)

\[
Pr(\mathcal{I}_t, x_{i,t} = 1) \cdot (\beta_i + \alpha_i(1) - 1) \geq Pr(\mathcal{I}_t, x_{i,t} = 0) \cdot (\alpha_i(0)),
\]

which is true if

\[ \alpha_i(1) \geq 1. \]  \hfill (2.2)

\(^1\)The interior of the probability term will generally be suppressed throughout this paper to make for less clunky notation. Always included are the relevant conditions of subjective probability for individual \( i \) at time \( t \).
The above equation states that a potential funder of altruistic type will fund a first dollar if the marginal altruistic utility of initial funding is greater than the marginal utility of income. The decision to fund a first dollar is hereafter referred to as the extensive decision.

A potential funder of altruistic type will continue to fund dollars until the point where

\[ Pr(\mid I_t, x_{i,t} = x_{i,t}^* + 1) \cdot (\beta_i + \alpha_i(x_{i,t}^* + 1) - 1) < Pr(\mid I_t, x_{i,t} = x_{i,t}^*) \cdot (\alpha_i(x_{i,t}^*)) , \]

which is true if

\[ \alpha_i(x_{i,t}^* + 1) - \alpha_i(x_{i,t}^*) < 1. \]

The above equation states that a potential funder of altruistic type will continue to fund additional dollars up until the point where the altruistic utility gained from additional funding is less than the marginal utility of income. The decision of funding level after the first dollar is hereafter referred to as the intensive decision. Note that both the extensive and intensive decisions are unaffected by project utility \( \beta_i \).

### 2.3.1.2 Decision-making by Altruistic Type Funders, Assumed to have Some Effect on Probability of Success

Expected utility for a potential funder of altruistic type assumed to have an effect on the probability of project success is equal to Equation 2.1. In this case an altruistic type will fund a first dollar if

\[ Pr(\mid I_t, x_{i,t} = 1) \cdot (\beta_i + \alpha_i(1) - 1) \geq Pr(\mid I_t, x_{i,t} = 0) \cdot (\alpha_i(0)) , \]

which is true if

\[ \left( 1 - \frac{Pr(\mid I_t, x_{i,t} = 0)}{Pr(\mid I_t, x_{i,t} = 1)} \right) \cdot \beta_i + \alpha_i(1) \geq 1. \quad (2.3) \]

The difference between the above equation and Equation 2.2 is the inclusion of the \( \beta_i \) term on the left hand side of Equation 2.3. This term in some sense allows for the marginalization of the project utility for a potential funder. A positive difference \( Pr(\mid I_t, x_{i,t} = 1) - Pr(\mid I_t, x_{i,t} = 0) \) may incentivize an altruistic type funder to make a positive extensive decision. Furthermore, the larger the difference, the smaller \( \beta_i \) is necessary to induce a positive extensive decision. In particular, consider the case of an altruistic type with \( \alpha_i(x_{i,t}) = 0 \ \forall \ x_{i,t} \), so that this individual will never make a positive extensive decision according to Equation 2.2. The ability to affect the probability of
successful project funding will then open up the possibility for more altruistic type funders to make a positive extensive decision. Thus, the expectation is that there will be more altruistic funders the greater is \(1 - \frac{Pr(|I_{\text{It}}, x_{i,t} = 0|)}{Pr(|I_{\text{It}}, x_{i,t} = 1|)}\), all else equal.

If an altruistic type is able to affect the probability of successful project funding, and has made a positive extensive decision, he will continue to fund additional dollars up to the point where

\[
\left(1 - \frac{Pr(|I_{\text{It}}, x_{i,t}^*|)}{Pr(|I_{\text{It}}, x_{i,t}^* + 1|)}\right) \cdot \beta_i + \alpha_i(x_{i,t}^* + 1) - \frac{Pr(|I_{\text{It}}, x_{i,t} = 0|)}{Pr(|I_{\text{It}}, x_{i,t}^* + 1|)} \cdot \alpha_i(x_{i,t}^*) < 1.
\]

Similar to the extensive decision, the intensive decision in this case depends on \(\beta_i\). Note that an altruistic type will continue to fund additional dollars as long as the incremental increases in the probability of successful project funding remain large enough. Thus, the expectation is that funding levels per altruistic type will be greater the greater is \(1 - \frac{Pr(|I_{\text{It}}, x_{i,t}^*|)}{Pr(|I_{\text{It}}, x_{i,t}^* + 1|)}\) \(|x_{i,t} > 1\), all else equal.

### 2.3.2 Expected Utility for Reward Type Funders

For any given project, expected utility for reward type funders is modeled as

\[
E[U_{i,t}|I_{\text{It}}, \beta_i, R_i, x_{i,t}] = \begin{cases} 
Pr(X_{i,t} + x_i \geq G|I_{\text{It}}, x_{i,t}) \cdot (\beta_i + R_i - x_{i,t}), & \text{if } x_{i,t} \geq P \\
Pr(X_{i,t} + x_i \geq G|I_{\text{It}}, x_{i,t}) \cdot (\beta_i - x_{i,t}), & \text{if } x_{i,t} < P,
\end{cases}
\]  

(2.4)

where all notation is the same as Equation 2.1 except \(R_i\) represents individual \(i\)’s utility from receiving the reward, and \(P\) represents the individual funding level necessary to receive the reward, or the price of the reward. The above equation states that each reward type funder receives utility \(\beta_i\) upon successful project funding, and receives utility \(R_i\) if individual funding levels are greater than or equal to \(P\). For reward types it is assumed that \(R_i > 0 \forall i\).

#### 2.3.2.1 Decision-making by Reward Type Funders, Assumed to have No Effect on Probability of Success

Expected utility for reward types is given by Equation 2.4, with the probability of successful project funding being independent of \(x_{i,t}\). Trivially, a reward type funder will only fund a positive amount if \(R_i > P\), and when this is true will only fund exactly \(P\). In this case, a crowdfunding
project is simply a market for the purchase of a binary good.²

2.3.2.2 Decision-making by Reward Type Funders, Assumed to have Some Effect on Probability of Success

A similar set of incentives to those faced by altruistic types are faced by reward types if they have an effect on the probability of successful project funding. In analyzing the decision-making of reward types, it is easiest to first consider how a reward type individual will choose to fund if no reward is offered. A reward type will make the decision to fund the first dollar if

\[ (1 - \frac{Pr(|I_t, x_{i,t} = 0|)}{Pr(|I_t, x_{i,t} = 1|)}) \cdot \beta_i \geq 1, \]

and will keep funding additional dollars until

\[ (1 - \frac{Pr(|I_t, x_{i,t}^*|)}{Pr(|I_t, x_{i,t}^* + 1|)}) \cdot \beta_i < 1. \]  

(2.5)

Consider now the additional choice to purchase a reward, and an individual with some positive \( R_i \). Trivially, if \( x_{i,t}^* \geq P \), then the reward type will choose to receive the reward. Also trivially, if \( R_i > P \) the reward type will choose to purchase the reward. The interesting case is where \( x_{i,t}^* < P \) and \( R_i \). Consider some \( R_i = P - \epsilon \). Then a reward type will choose to purchase the reward if

\[ Pr(|I_t, x_{i,t} = P|) \cdot (\beta_i + R_i - P) \geq Pr(|I_t, x_{i,t} = x_{i,t}^*|) \cdot (\beta_i - x_{i,t}^*). \]

Plugging \( P - \epsilon \) in for \( R_i \), and after some math, a reward type funder will purchase the reward if

\[ \beta_i + \frac{Pr(|I_t, x_{i,t} = x_{i,t}^*|)}{Pr(|I_t, x_{i,t} = P|)} \cdot (x_{i,t} - \beta_i) \geq \epsilon. \]

Note that a reward type funder would never have chosen an \( x_{i,t}^* > \beta_i \) in Equation 2.5, and thus the left hand side is greater for a smaller \( \frac{Pr(|I_t, x_{i,t} = x_{i,t}^*|)}{Pr(|I_t, x_{i,t} = P|)} \), and thus a bigger difference between this ratio, the more likely a reward type funder is to purchase the reward.

Similar arguments given for the intensive decision by altruistic types applies to reward types

²In Kickstarter, any one funder must choose a single reward. While it would be possible to set up multiple accounts, and in doing so gain the ability to purchase a quantity of some particular reward greater than one, this possibility is disregarded for simplicity.
and so will not be repeated. As for the case with altruistic types, reward types are more likely to make a positive extensive decision and fund more in the intensive decision the greater the ability to affect the probability of successful project funding. Also, for both reward and altruistic types, the extensive decision will only be increased due to an ability to affect the probability of project success through the presence of project utility. If \( \beta_i = 0 \), there is no ability to affect probability that will incentivize a reward or altruistic type to make a positive extensive decision when they would otherwise contribute zero.

### 2.3.3 Funding Dynamics of Project Fund-Raising Duration

The theory presented above assumes that the probability of project success changes with the funding dynamics of a particular project. For example, a project that has raised 50% of their goal on the first day of funding should be more likely to ultimately succeed as opposed to a project with 50% of their goal left on the last day of the funding period. Contributions made at different times, towards projects at different funding levels, aren’t expected to have the same impact on the probability of ultimate project success.

Funding and networking activity early in the fund-raising period may have a larger impact on ultimate success insofar as this early behavior transmits information about the project across potential funders. Agrawal et al. (2011) and Conti et al. (2013) have found that family and friends make up much of the earliest funding, and that this type of funding is an important determinant of project success. Agrawal et al. (2015) finds that the propensity to invest in a particular project increases with total funds raised. Bardsley and Sausgruber (2005) argues that reciprocity amongst potential investors explains some portion of this type of crowding in behavior. Conti et al. (2013) attributes this phenomenon in investor signaling to family and friends acting as a commitment device, signaling the trustworthiness of the fund-raiser. Beyond initial contributions, the building of a network of informed potential funders at the beginning of the fund-raising period may also be important. Giudici et al. (2013) and Kromidha and Robson (2016) find that the social capital of the project creator, and thus the initial network available for creating potential funders, is also an important determinant in ultimate project success.

The theory presented in this paper, with the previous findings above, suggests that funding levels should be higher at the beginning of the fund-raising period, and highest at the end if the project is not yet fully funded. While this is generally true, there is also a common decrease in
funding during the middle of the fund-raising period, followed by a return to high levels of funding, creating a U-shaped profile of contribution dynamics across time. This dynamic may be simply due to Kickstarter pushing for visibility of projects within the Kickstarter page at the beginning and end of fund-raising periods. While Kickstarter does increase visibility of new and ending fund-raising periods, Kuppuswamy and Bayus (2015) finds that the U-shaped funding profile is not due to visibility, but to previous funding levels, with high periods being followed by low periods throughout the duration. Burtch et al. (2013) finds that there are substitution effects between contributors, with the marginal utility of contributing decreasing with others contributions. Agrawal et al. (2013) postulates that this is due to a bystander effect, or that individuals wait for other contributors to fund the project at no cost too themselves.

This paper explains the funding profile as a product of individual decisions based on the ability to affect the probability of project success. The ability to affect project success is high at the outset of the fund-raising period due to the importance of signaling and network creation. Once a certain probability of success is reached, there is a slowdown in funding due to a decreased ability to affect success. However, the probability of success decreases, and the ability to affect success increases, as the fund-raising period moves on with the same or similar funding levels. This dynamic incentivizes potential funders to contribute towards the end of the period.

2.4 Data and Empirical Methodology

Following from the theory section of this paper, potential funders will make funding and reward decisions based upon a subjective probability that a project will be successfully funded. These decisions are made with the information set available to the potential funder on day $t$. Certain information available to potential funders is static and remains constant across time, while other information may change over the course of the project’s fund-raising period. Project page characteristics comprise the static information available to a potential funder. These characteristics include any videos posted, the description of the project, any images posted, the genre of the project, and the funding goal. These page characteristics are used as a base indicator of project quality by the potential funders. The previous actions of funders comprises the dynamic information available to present funders. This information includes how many previous individuals have funded the project, the total amount of funding the project has received and thus how much additional funding is re-
quired, and how many times the project has been shared over the social network platforms Facebook and Twitter. The empirical strategy of this paper is to estimate the subjective probabilities faced by potential funders, and to relate these subjective probabilities to the number of funders for a project and the dollar amounts pledged using reduced form panel data estimation.

2.4.1 Empirical Methodology

2.4.1.1 Estimating the Subjective Probability of Project Success

The probability that a particular project will be successfully funded by the end of the fund-raising period is modeled using the logit specification. Then the probability of success can be parameterized as

\[
Pr(X_j \geq G_j | I_{j,t}) = \frac{e^{\sigma + \theta Z_j}}{1 + e^{\sigma + \theta Z_j}},
\]

(2.6)

with

\[
\sigma = \phi_{1,t} \cdot \text{sharesper}_{j,t} + \phi_{2,t} \cdot \text{backersper}_{j,t} + \phi_{3,t} \cdot \text{fundingleft}_{j,t},
\]

and \( j \) indexes projects and \( t \) denotes the day in the funding duration. The variable \( \text{sharesper}_{j,t} \) measures the number of Facebook shares per dollar of unfunded project goal for project \( j \) on day \( t \), and represents the market size of potential funders which may be willing to cover the unfunded costs in the future. It is expected that \( \text{sharesper}_{j,t} \) has a positive effect on probability of successful project funding. The variable \( \text{backersper}_{j,t} \) measures the number of prior backers per dollar of unfunded project goal for project \( j \) on day \( t \), representing a pool of funders with positive value over the project that may be willing to commit additional funds in the future in order to complete funding of the project. It is expected that \( \text{backersper}_{j,t} \) will also have a positive effect on probability of successful project funding. The variable \( \text{fundingleft}_{j,t} \) simply measures the unfunded project goal in dollars for project \( j \) on day \( t \), with the expectation of a negative affect on the probability of successful project funding. All of the dynamic variables of interest are observed at the beginning of day \( t \), and thus the logit specification above will estimate the probability of eventual project funding success at the beginning of every day in the fund-raising period. The vector \( Z_j \) represents static characteristics of project \( j \). It is assumed in this empirical analysis that all potential funders hold an expectation about the probability of successful project funding equal to the empirical results of the logit specification presented above. Separate logit regressions are run for each day in the project.
duration period excluding the first day.\footnote{The first day of the fund-raising period is omitted as it isn’t possible to construct marginal effects of additional dollar funding using only the static project characteristics.}

In accordance with the theory presented above, a proxy variable for the effect that a funder has on the probability of project success by funding dollars on day \( t \), for project \( j \), is constructed as

\[
probeffect_{j,t} = 1 - \frac{Pr(\text{funding}_{j,t} = 0)_{j,t}}{Pr(\text{funding}_{j,t} = 1)_{j,t}},
\]  

or one minus the ratio of the fitted probability of success for project \( j \) if there are zero additional funds on day \( t \), over the fitted probability of success for project \( j \) if there is one dollar in additional funding on day \( t \). A dollar of additional funding will change all three dynamic variables in Equation 2.6. The purpose of the proxy variable \( probeffect_{j,t} \) is to characterize the ability that potential funders have to affect the probability of success for project \( j \) during day \( t \).

### 2.4.1.2 Estimating the Effect on Daily Funding Levels Due to Ability to Affect Probability of Project Success

A reduced form, fixed effects regression model is employed in order to identify the effect on daily funding levels due to an increased ability to affect the probability of successful project funding. The reduced form model is parameterized as

\[
funding_{j,t} = \lambda_1 \cdot probeffect_{j,t} + \kappa_1 \cdot \text{newfunders}_{j,t} + \beta \cdot W_{j,t} + \nu_j + \mu_t,
\]

where \( probeffect_{j,t} \) is defined by Equation 2.7, \( \text{newfunders}_{j,t} \) is the number of new funders for project \( j \) on day \( t \), and \( W_{j,t} \) includes variables controlling for project quality signals that may change over time. These controls include number of previous backers per day, previous Facebook shares per day, and previous amount raised per day. A positive level for \( \lambda \) would provide evidence that, controlling for the number of new funders, funding levels are higher the greater is the ability to affect probability of success.

Ideally, the independent variable in Equation 2.8 would be additional funding per funder, rather than total funding controlling for the number of new funders. This isn’t possible because funding on any day for a particular project may either be negative or positive with no change in the number of funders.\footnote{This is because funders are able to add or withdraw funding on any day other than the last day, where withdrawing}

Other research seems to have dealt with this issue by cleaning up the data.
in some fashion, but that would be unavoidable for the purposes of this paper. While infrequent, approximately 4.5% of project-day observations have some positive value for $funding_{j,t}$ with no change in the number of funders. Furthermore, prior funders changing their funding level holds important information as it might be expected that funders will reduce funding levels if the project subsequently becomes highly probable to be successful without their funding.

### 2.4.1.3 Estimating the Effect on Daily Number of Funders Due to the Ability to Affect Probability of Project Success

A reduced form, fixed effects regression model is also employed in order to identify the effect on daily number of funders due to an increased effect on the probability of project success. The reduced form model is parameterized as

\[
newbackers_{j,t} = \lambda_2 \cdot probeffect_{j,t} + \kappa_2 \cdot newshares_{j,t} + \psi \cdot W_j, t + \zeta_j + \eta_t, \tag{2.9}
\]

where $probeffect_{j,t}$ is again defined as Equation 2.7, $newshares_{j,t}$ is the number of new Facebook shares on day $t$, and $W$ are the same dynamic quality signal variables as in Equation 2.8. Similar to the case of negative values for $funding_{j,t}$, $newbackers_{j,t}$ is infrequently negative. For the same reasons given above, these data points are not cleaned as they may hold valuable information.

### 2.4.2 Data

The data used in this study were acquired from Kickspy.com, which were themselves collected from publicly available information on the Kickstarter.com website. The data include all projects with a 30 day fund-raising duration period in which the fund-raising period was complete, whether successfully funded or otherwise, for the two month period encompassing February 1, 2014 to March 31, 2014.\(^5\) Considering only projects with a fund-raising period of 30 days allows for complete day fixed effects in the reduced form models, which is important due to possible funding dynamics across time not captured by included determinants. Projects receiving no funding over the course of the project duration, as well as projects with a goal of less than $500 or more than $250,000 are left out of the sample.\(^6\) There are a total of 1,136 projects fitting this description in

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\(^5\)Some projects are canceled by the project creators, with no indication for why this has occurred.

\(^6\)There are projects of very large goal levels, none of which are successful. These large projects, as well as projects small enough to be realistically funded by one individual, are left out of the sample.
the dataset.

The data include static as well as dynamic information for each of the 1,136 projects. Static information on projects includes project genre, the number of videos and images on the project page advertising and explaining the project, the number of words in the text description of the project, the goal level, and if the project was ultimately successful. Table 6 presents statistics on project funding success by genre. There is a good deal of variation in the number of projects by genre, as well as the success rate of different genres. The most frequent project types are Film and Music, while the most successful genre is Comics, with 67.3 percent of created projects ultimately being funded. At the other extreme, the least successful genre is Fashion, with 32.8 percent of projects being fully funded. Project genres are included as dummy variables in the logit regressions run for the results in this paper.

Figure 4 presents a histogram of final amount raised, minus the goal level, for each project that falls within $7,000 dollars from the goal in both directions\(^7\). The mass of projects at or slightly above zero suggests that those with funding levels close to the goal are very likely to be successful, and also unlikely to raise funds in great excess of the goal. This type of funding behavior provides some evidence that Kickstarter is working as a type of subscription game mechanism, although it could also be the case that project creators are good at picking goal levels in accordance with actual aggregate willingness to pay for their project.

Table 7 presents mean values and standard deviations for static project page characteristics by the success of projects. Successful projects are smaller, in terms of goal levels, than unsuccessful projects on average. The indicators for project quality all display higher mean values for successful projects, going some way in justifying their inclusion in the logit regressions for such purposes. Previous studies have also found that these page characteristics are correlated with eventual project success.

Daily level dynamic information for projects used in this analysis includes overall funding levels, the number of funders, and the number of Facebook shares for a particular project. Figure 5 presents the time dynamics of mean daily funding levels for Kickstarter projects in the dataset. Mean daily funding levels for projects follow a common U-shape found by previous studies on

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\(^7\)There are certainly projects that never get off the ground and are further away than $7,000 from their project goal. There are also projects that exceed their goal in raised funds by more than $7,000. Figure 4 contains approximately 68% of all projects, and is intended to show dispersion of raised funds around the project goal for values close to the goal.
Kickstarter, as already discussed. This commonality in funding dynamics across projects points to the importance of controlling for day in the fund-raising period in the estimation of the reduced form models. Figure 6 presents the same dynamic graph for the mean number of new funders by day in the project duration. Not surprisingly, we see the same overall U-shape as in Figure 5, likely due to the same phenomena. Figure 7 presents the ratio of mean additional daily funding to mean additional daily funders. We do not see the same U-shape found in the previous two figures, with this ratio increasing at the outset, and then falling towards the end of the funding period.

Table 8 presents summary statistics for dynamic variables of interest in the logit specification. Covariate values are at the day-project level for projects in which the goal has yet to be reached. The mean of \( \text{sharesper}_{j,t} \) is equal to 0.18, which equates to an average level of unfunded cost per Facebook share equal to $5.54. The mean of \( \text{backersper}_{j,t} \) is equal to 0.036, which equates to an average of $27.61 of unfunded cost per prior backer. The mean level of \( \text{fundingleft}_{j,t} \) is equal to $12,017, with a large amount of variation in the sample. This variation is unsurprising considering the variation in original goal levels across projects.

As the dynamic variables of interest in the logit specification change over time, it is instructive to investigate the dynamics of these changes. Figure 8a presents mean values for \( \text{sharesper}_{j,t} \) over time. The value of \( \text{sharesper}_{j,t} \) steadily increases over time through project funding, as well as through increasing Facebook shares. There are two large jumps in \( \text{sharesper}_{j,t} \) towards the end of the project duration as there is a final push for funding. Comparing Figure 8a to Figure 8c shows that the first large increase towards the end of the project duration is not due to decreasing unfunded costs, as unfunded costs remain at similar levels until an increase at the end. The graphs suggest that there is a push for funding a few days before the fund-raising period ends, in which many projects become fully funded, leaving a group to push for funding on the last day. Figure 8b tells a similar story for \( \text{backersper}_{j,t} \) as \( \text{sharesper}_{j,t} \). Towards the end of the project duration, there is a large increase in \( \text{backersper}_{j,t} \) unmatched by a sudden decrease in unfunded costs. A last push for funding is made on the last day of the project duration. Unfunded costs, or \( \text{fundingleft}_{j,t} \), falls steadily over the course of the funding period, with a sharp increase towards the end as many projects become fully funded, leaving a selection of mostly unsuccessful, low value projects.

\[8\] Ideally this analysis would be for mean daily funding per funder. However, as previously explained, there are quite a few days for different projects in which funding is either positive or negative and there is zero change in the number of funders.
2.5 Results

2.5.1 Logit Regression Results

Logit regressions are run for each day in the project funding period, excluding the first day, in which the dependent variable is a binary one indicating whether the project is successfully funded at the end of the fund-raising duration. Due to the volume of results from running 29 different logits, they are presented in graphical form. Figures 9a and 9b paint a picture of the relative importance of different activity as the fund-raising period commences. At the outset it is important to develop Facebook shares in order to increase the market size of potential funders for the rest of the fund-raising period. At days 2 – 3 it is estimated that a 1% increase in sharesper leads to a 5 percentage point increase in expected probability of successful project funding, on average. However, it quickly becomes relatively more important that these shares be turned into actual funders, and this importance is sustained for a longer duration than with sharesper. From day 7 through 15 the semi-elasticity for backersper hovers at approximately 7, with the same interpretation as that given for sharesper. Both determinants become less important as the fund-raising period comes to a close, but always remaining positive and never becoming statistically insignificant.

As stated earlier, a proxy variable for the effect that a potential funder has on the probability of project success is constructed from the logit regression results according to Equation 2.7. Figure 10a presents mean values for probeffect across all projects. The proxy variable begins the fund-raising period at a moderate level, dipping to a relatively low level, before increasing to a maximum during the second half of the funding duration. Figure 10a shows probeffect dropping as the fund-raising period ends, but this is mainly being driven by projects that are already successfully funded. The value for probeffect is necessarily zero for these projects, and more projects become fully funded over time. Figure 10b shows that this drop in probeffect is not apparent when excluding projects that are already fully funded, hitting a high and remaining at approximately these levels for the whole of the second half of the fund-raising period. The values for probeffect are relatively small, and thus we may expect the results from the reduced form regressions to also be small in economic terms. For ease of inference, probeffect will be scaled up by a factor of 1000 for reduced form model estimation purposes.
2.5.2 Reduced Form Model Results

Results for both reduced form models are presented as Table 9. The estimation results for Equation 2.8 are presented on the left-hand side of Table 9. The coefficient on probeffect is statistically significant at the 10% confidence level with an economically small effect. A one standard deviation increase in probeffect results in an increase of approximately $28 in expected total funding per day. This effect is small relative to the unconditional mean level of funding of per day of $381. Unsurprisingly, the control variable newbackers is statistically significant and positive, with an increase in expected funding of $55.48 for each funder. The presence of previous funders reduces expected present funding levels by $3.50. While this result for previous funders is in agreement with other research, the logic behind the result, namely that with more funders one individually need not fund as much in order to successfully fund the project, leads one to believe that the negative effect of previous funders would disappear with the inclusion of probeffect.

The estimation results for Equation 2.9 are presented on the right-hand side of Table 9. The results for the effect of probeffect on newfunders is statistically significant at the 5% confidence level, but similar to the case with effects on funding levels, the effect in economic terms is weak. A one standard deviation change in probeffect is estimated to increase the expected number of new funders per day by approximately 0.67 on average. The coefficient on prevfunders is statistically insignificant in this case. New Facebook shares has a positive and significant effect on new funders, as would be expected. A coefficient value of 0.146 on newshares implies that the expected number of new funders increases by a funder for every 7 new Facebook shares.

2.6 Conclusion

This paper finds evidence that potential funders are aware of, and react to, opportunities for increasing the probability that a desired project is ultimately successful. These effects are rather muted however, and probably make up a small part of the behavior of potential funders. It may be the case that small projects largely depend on altruistic funding from a small network of family and friends, while large projects are generally functioning as pre-order mechanisms with little ability to affect success by any one individual. These results also suggest that some portion of the U-shaped funding profile is explained by potential funders contributing when the ability to affect success is high, but that much of it can be explained by the visibility preferences of Kickstarter.
Further research into crowdfunder behavior might characterize in a richer way the expectations of project creators with respect to the expected pool of potential funders at their disposal. Namely, while the economically small results of this paper suggest that the motivation for project success is somewhat unimportant overall for funders, it might be the case that project creators are setting goal levels that don't require potential funders to pay more than just their reward and altruistic utilities would suggest. Furthermore, if there is a large cost to setting up an effective project page, project creators may be unwilling to invest into projects in which overall demand for the project is likely to be close to the goal realistically necessary for implementation of the project once funded.
Chapter 3

Ex Ante Inefficiency of a Simple Subscription Game for the Voluntary Provision of a Public Good with Incomplete Information and a Monopoly Provider

3.1 Introduction

The provision of public goods in an economy has long been a subject of interest to economists. A great deal of research has been done on the topic of public goods provision since the formalization of inefficiencies inherent in the market provision of public goods found in Samuelson (1954), and the extension into the individual incentives behind collective action in Olson (1965). One strain of this continuing research agenda focuses on the efficiency of different mechanisms for the voluntary provision of discrete public goods. The focus of this research has generally been on developing simple mechanisms for the collection of funds, proving the existence of equilibria that exists within these mechanisms, and reporting the efficiency results. The majority of this research considers either a
centralized or de-centralized collector of funds and, implicitly or explicitly, assumes this collector to be benevolent in the sense that they simply collect funds and subsequently spend these funds on the provision of some public good. The purpose of this paper is to consider a more cynical possibility where the collector of funds is a profit maximizing entity, and what effects a collector of this type may have on the ex ante inefficiency of a relatively simple contribution game. Furthermore, the game developed in this paper allows for comparisons of ex ante inefficiency for different economic environments. This paper finds that ex ante inefficiency decreases with market size, but increases as the cost of the public good or the scale of the good increases. Ex ante inefficiency increases if the public good provider is a monopolist, with absolute losses in efficiency being greater the more efficient the outcomes under a benevolent provider, and relative efficiency levels between the two providers remaining stable across different economic environments.

The most successful early attempt at constructing a mechanism for the efficient provision of public goods was suggested by Groves and Ledyard (1977). However, their mechanism requires a central collecting agent with the ability to impose participation in the game, as well as a complex taxing and subsidy system, based on signals provided by the population, to be performed by the collector. Attempts to devise simpler mechanisms that may not require a coercive collecting agent led to the consideration of mechanisms for the voluntary provision of discrete public goods, sometimes with rebate rules. In the literature, a contribution game with a rebate rule is known as a subscription game, while a game without a rebate rule is simply known as a contribution game. Palfrey and Rosenthal (1984) show that, in a simple game with complete information and binary funding rules, contributions towards a discrete public good are greater with a rebate rule than without. Bagnoli and Lipman (1989) allow for continuous contributions in a similar subscription game and show that all undominated perfect Nash equilibria are efficient in that they reveal the core of the economy. Admati and Perry (1991) finds similar efficiency results investigating a dynamic subscription game with complete information.

While the results in papers such as Bagnoli and Lipman, and Admati are promising, they

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1 This paper defines ex ante efficiency as the probability that an ex post efficient outcome is attained.
2 A rebate rule requires that contributions towards the funding of a discrete public good be returned if the provision point of the public good is unmet.
3 This is an example of an all-or-nothing game, only allowing for one contribution level.
rest on the assumption of complete information. Studies have shown that the voluntary provision of a public good will be ex ante inefficient in the presence of incomplete information for both dynamic and static games.\textsuperscript{4} Due to the nature of necessary ex ante inefficiency in the presence of incomplete information, many studies have adopted the notion of interim incentive efficiency proposed by Holmström and Myerson (1983). A decision rule, or institution, is interim incentive efficient if there is “no other decision rule that can be found that may make some individuals better off without ever making any other individuals worse off” (Holmström and Myerson (1983)). Thus, interim incentive efficiency is concerned with judging mechanisms for allocation, and whether there exists a “better” mechanism for organizing decision-making amongst agents with asymmetric information. A good deal of interim incentive efficient mechanisms have been found for the private provision of public goods in the presence of incomplete information.\textsuperscript{5}

This paper takes as given the classical ex ante inefficiency of public goods provision in the presence of incomplete information and investigates how this inefficiency changes with differing market conditions and for different provider types. The mechanism identified as interim incentive efficient in Lu and Quah (2009) is utilized as the mechanism for fund provision.\textsuperscript{6} Namely, a monopoly provider posts a cost of provision, potentially greater than the true cost, for some public good and individuals make simultaneous contributions to said provision. The public good is provided if contributions meet or exceed the posted cost, and returned otherwise. The ex ante efficiency of this subscription game is compared to ex ante efficiency when the provider is benevolent, or posts a cost for the public good equal to the true cost. Furthermore, ex ante efficiency of the subscription game is compared across different economic environments, including market size, cost of public good, and scale of the public good.

Interim incentive efficiency has been studied for a monopolist provider of a public good, finding that such situations may be interim incentive efficient,\textsuperscript{7} but to my knowledge this is the first study to investigate ex ante inefficiency in the presence of incomplete information and a monopoly provider of a public good. While it is certainly valuable to identify interim incentive efficient mech-

\textsuperscript{4} See Gradstein (1992), Menezes et al. (2001), Laussel and Palfrey (2003), and Barbieri and Malueg (2008).
\textsuperscript{5} See Gradstein (1994), Laussel and Palfrey (2003), Barbieri and Malueg (2008) and Lu and Quah (2009) for examples.
\textsuperscript{6} Albeit with slightly different assumptions in the model.
\textsuperscript{7} See Alboth et al. (2001), Lu and Quah (2009), and Barbieri and Malueg (2010) for examples.
anisms, an understanding of how ex ante inefficiency may be affected by market conditions and
provider type when using an interim incentive efficient mechanism is also of value. This paper adds
to the literature on the ex ante inefficiency of voluntary public goods provision by providing evidence
when such mechanisms may be viable, as well as the efficiency costs of monopoly providers in such
markets. The rest of the paper is outlined as follows: section 2 informally discusses the subscription
game of this paper and provides justification; section 3 describes the formal setup of the subscription
game; section 4 outlines equilibrium behavior of contributors in the subscription game while section
5 does the same for a monopoly providers; section 6 briefly details the analytical technique used to
derive equilibrium outcomes and evaluate ex ante efficiency of the game; section 7 presents results
and section 8 provides concluding remarks.

3.2 Informal Discussion of Subscription Game

One purpose of this paper is to compare efficiency results for monopolist and benevolent
providers. A benevolent provider is defined as a provider that posts the true cost for some public
good, collects contributions, and refunds contributions if the cost of the public good is unmet by
said contributions.\(^8\) Let a monopoly provider be defined as following the same guidelines as the
benevolent provider in terms of collecting and refunding contributions, but a monopoly provider
may post any cost for provision of the public good. Note that the true cost of providing the public
good may be known to all agents in the game, although in many realistic situations this true cost
may be unknown to all potential contributors.

At first glance it may seem that there aren’t many real world examples approximating this
situation, however there are quite a few realistic situations in which the provider of a public good
could be considered a monopolist. The first example I will outline, and possibly the most obvious
to the reader, is the case of local governments. The classic provision of a streetlight provides a good
example. A group of citizens, potentially one street, desires to put up a streetlight which will serve
as the discrete public good. In classic interpretations of this example, the cost of the streetlight is
either truthfully reported to the citizens, or is in some sense implicitly known by the citizens, and

\(^8\)Note this means that the benevolent provider is budget neutral, or they will not cover any unmet costs for public
good provision.
if contributions reach this cost, the streetlight is constructed and the benefits are enjoyed by the citizens. If the local government, particular works department involved, or, generally speaking, the arbiter of provision and poster of costs is a profit maximizer, the efficiency results for the provision of this public good may be affected.

Charitable organizations comprise the second example. Meals-on-wheels is a popular local charity in the United States which delivers food to indigent or immobile individuals. Meals-on-Wheels works by servicing routes, or driving to different homes in certain localities. In order to open a new route, Meals-on-Wheels may choose to hold a fund-raiser. The posted cost required to run this route may be different from the true cost if Meals-on-Wheels is a profit maximizing provider of this type of service.

The third, and final example, comes from the recent technological innovation of crowdfunding. “The Drive-Thru with Rog 2014 Season” was a crowdfunding campaign on the popular online platform Kickstarter in January of 2014. The purpose of the “Rog” campaign was to raise funds so that a bluegrass music radio show could remain on the air for another season. Insofar as the “Rog” radio show is differentiated from other area shows, then there is the possibility that “Rog” enjoyed market power in his fund-raising campaign. If this is the case, “Rog” may have chosen to post a cost for the next season’s radio show greater than the true cost of running the show.

The subscription game presented in this paper is made relatively simple through assumptions and a focus on a narrow class of equilibria. Most similar subscription games are constrained to investigating 2-player games due to the levels of complexity inherent in allowing for a broader range

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9I use Meals-on-Wheels as my example because of my personal experience working with them on philanthropic endeavors. The point of this paper is certainly not to single out any individual charity, and I believe personally that Meals-on-Wheels is a noble organization.

10The example presented here is in some sense one of a partial-equilibrium. It is beyond the scope of this paper to examine the general equilibrium competition effects of any charitable works industries. Previous studies have found that competition within philanthropic and non-profit industries drive discretionary spending and income within those industries. See Feigenbaum (1987) for an example of the effects of competition in the U.S. medical research industries on passthrough rates and expense-preference activities on the part of the charitable organization.

11The mechanism employed by Kickstarter for raising funds shares many similarities with the mechanism found in this paper. There is a provision point provided by a content creator that then raises pledges to contribute from a population of potential funders. If these pledges exceed the provision point supplied by the creator, then all pledges change hands to the creator and the project is realized by the creator. If pledges fail to meet the provision point then no pledges change hands and the project is not realized. Major differences between Kickstarter’s mechanism and the one presented in this paper are that Kickstarter raises funds over time and not simultaneously, as well as offering private rewards to individual funders based on their individual contribution levels.
of strategies and equilibrium concepts. (Barbieri and Malug (2008)) The benefits of restricting the consideration of equilibria in the subscription game are in allowing for calculation of ex ante efficiency, including in markets with potentially many players. The costs of the restrictions are readily apparent, as allowing for a richer set of equilibrium concepts may in some way change the set of equilibria and thus the results of the paper.

3.3 Formal Setup of the Subscription Game

In the first stage of the subscription game, or the posting stage, a discrete public good becomes available for which either a benevolent or risk-neutral monopoly provider may supply. The provider subsequently acts as the collector in the second stage of the subscription game. This game assumes as exogenous the availability of providing the public good on the part of the provider. The provider is also made aware of the true costs, hereafter $C_t$, of providing the discrete public good. The provider then posts a public cost of supplying the good which, if contributions meet or exceed, will subsequently be provided to a population. Finally, each risk-neutral individual in the population, or market, the size of which is hereafter $N$, receives an independent value draw over completion of the project. These value draws follow a Bernoulli distribution, with each individual in the population receiving a positive value over completion of the project, $V$, with probability $p$, or a value of 0 with probability $1 - p$. The value of $p$ is common knowledge amongst all players in the game and make up the prior belief structure. This distribution leads to two types of individuals in the market, value 0 and value $V$ types. Individuals with a value of $V$ are hereafter referred to as type $G$. Trivially, value 0 types will always contribute zero dollars to the provision of the public good and receive zero benefits from the completion of the project. The analysis in this paper disregards type 0 individuals for the rest of the contribution game with no effect on the outcomes.

The second stage of the contribution game, or the contribution stage, consists of all individuals in the market making voluntary contributions to the provision of the public good according to a utility function for individual $i$ given as

$$U_i = (V - x_i)$$
if contributions meet or exceed some \( C \), and zero otherwise. The variable \( x_i \) represents the contribution amount for individual \( i \). An assumption of a constant marginal utility of income equal to one normalizes the utility function. Furthermore, it is assumed that individuals are not budget constrained with regards to any desired funding level, \( x_i \).

In the third stage of the contribution game, or provision stage, the provider supplies the public good to the market if the aggregate level of contributions exceeds the posted cost. Any excess funds are kept by the provider. If the contribution level falls short of the posted cost, all contributions are returned to the contributers. An efficient ex post outcome at this stage of the game is one in which the provider supplies the public good, conditional on there being aggregate value over the public good equal to, or in excess of, the true cost of providing the public good. Contributions in excess of the posted cost that are kept by the provider are considered a simple transfer, and have no effect on efficiency.

3.4 Contribution Stage Equilibrium Analysis

The natural place to start in defining equilibrium outcomes of the contribution game is at the contribution stage, as the provision stage simply follows a group of rules, with no choices made by any agent. The analysis below defines symmetric pure strategy Bayesian Nash equilibria for any possible values of \( C \).\footnote{The analysis of this type of equilibrium is the focus in this paper.} This paper uses a technique similar to that found in Menezes et al. (2001), but simplified.

A symmetric pure strategy Bayesian equilibrium (BNE) entails that all individuals of type \( G \) contribute the same amount at equilibrium. Consider a contribution level for type \( G \) individuals equal to \( \frac{C}{n} \), where \( n \) is the minimum number of individuals of type \( G \) in market size \( N \) for contributions to meet or exceed \( C \). For any value of \( C \), \( p \), \( N \), and \( h \), the subjective probability that contributions meet or exceed \( C \) in the contribution stage for a type \( G \) individual contributing \( \frac{C}{n} \) is equal to

\[
P_n = \sum_{k=n-1}^{N-1} \binom{N-1}{k} p^k (1-p)^{N-1-k}.
\]
The equation above simply states that the probability contributions meet or exceed $C$ is equal to the probability of there being at least $n - 1$ other individuals of type $G$ in the market. Given the above probability, funding level $\frac{C}{n}$, and individual value over the project of $V$, the expected utility for an individual of type $G$ contributing $\frac{C}{n}$ is given as

$$E[U_i|V, C, p, N, n_i, n_{-i}] = (V - \frac{C}{n}) \cdot P_n.$$  \hfill (3.1)

The variable $n$ defines a contribution level, conditional on $C$, in the above expected utility function. Strategies for individuals of type $G$ can then be characterized by $n$ such that $n \in \mathbb{R}^+$. At this point it is helpful to separate the strategy space for individuals of type $G$ into two categories. Consider some $n = h_0$, such that $(N-1) \cdot \frac{C}{V} < h_0$. If all individuals of type $G$ play $h_0$, the subjective probability of successful funding, and expected utility, for some individual $i$ are both equal to zero due to the fact that an individual of type $G$ will never attempt to complete funding of the public good if this requires a contribution level greater than $V$. Weak best responses for any type $G$ individual in this case includes any $x_i \in \mathbb{R}[0, N \cdot \frac{C}{h_0} - C)$, which necessarily includes the $x_i$ corresponding to $h_0$. There is thus a set of symmetric BNE given as $H_0 = \{h_0|h_0 \in \mathbb{R}^+ \cap (N-1) \cdot \frac{(N-1) \cdot C}{C-V} < h_0\}$. Trivially, there is also a symmetric BNE at $x_i = 0$ if $V < C$.\footnote{It is assumed that $V < C$, or that no one individual has an incentive to fund the public good on their own.} Due to the fact that expected utility is zero for all of these symmetric pure strategies, they are hereafter referred to as the null set.

Disregarding the null set leaves for consideration strategies $n = h$, where $\{h|h \in \mathbb{R}^+ \cap h \leq \frac{(N-1) \cdot C}{C-V}\}$. While possible values for $h$ are uncountable, the following lemma shows that there are relatively few symmetric pure strategies $h$ that are incentive compatible.

**Lemma 1.** For a contribution stage in which $C \leq N \cdot V$,\footnote{It is assumed that $C \leq N \cdot V$ to disregard possibilities that aggregate willingness to pay for the public good can never meet the cost.} the only incentive compatible symmetric pure strategies, $h$, are positive integers in the range $\left[\frac{C}{V}, \frac{(N-1) \cdot C}{C-V}\right]$, or $\{h|h \in \mathbb{Z} \cap C \leq h \leq \frac{(N-1) \cdot C}{C-V}\}$. \hfill (3.1)

**Proof.** First, consider an integer value $h$ and some $\mu$, where $\mu \in (0, 1)$. Define $P_{h-\mu}$ as the probability of successfully funding the public good if all individuals of type $G$ contribute $\frac{C}{h-\mu}$. Given the nature
of the binomial distribution, it is the case that \( P_h = P_{h-\mu} \).\(^{15}\) There then must be an \( \epsilon \) such that
\[
(V - \frac{C}{h-\mu} + \epsilon) \cdot P_h > (V - \frac{C}{h-\mu}) \cdot P_h.
\]

It is then the case that a type \( G \) individual has an incentive to deviate away from a funding level of \( \frac{C}{h-\mu} \) by some amount \( \epsilon \).\(^{16}\)

Secondly, incentive compatible \( h \) can’t include integers less than \( \frac{C}{V} \) as this would imply type \( G \) individuals contributing more than their value for the public good. Type \( G \) individuals will contribute zero rather than some \( \frac{C}{h} > V \) as long as there is a positive probability that the public good will be funded, which is assured due to \( C \leq N \cdot V \).

Any valid equilibrium value for \( h \) must satisfy individual incentive constraints for type \( G \) individuals in the market. While possible deviations away from a particular \( h \) are uncountable, what follows below reduces these possibilities to a finite set of reasonable deviations, and uses these to construct simple incentive constraints for contributing less than, or greater than some value \( \frac{C}{h} \).

### 3.4.1 Downward Deviation Incentive Constraint

Possibilities for downward deviations away from a contribution level of \( \frac{C}{h} \) are uncountable. First, an incentive constraint for a downward deviation to an individual contribution level of zero is given, and then it is shown that a deviation to a zero contribution level is the only relevant one to consider.

Consider some type \( G \) individual \( i \) and assume that all other individuals of type \( G \) are playing strategy \( h \). If individual \( i \) deviates from a contribution level of \( \frac{C}{h} \) to zero, the subjective probability of successful funding for individual \( i \) is given by
\[
P_{h-1} = \sum_{k=h}^{N-1} \binom{N - 1}{k} \cdot p^k \cdot (1 - p)^{N-1-k},
\]
\(^{15}\)For example, if \( h - \mu = 2.5 \), then the minimum number of type \( G \) individuals necessary to successfully fund the public good is equal to 3, as there is no possibility of attaining a half of a type \( G \) individual.
\(^{16}\)The optimal deviation is equal to \(-\frac{C}{(h-\mu) \cdot \mu}\). What is important however, is that there exist some deviation that makes unreasonable non-integer values for \( h \).
or the probability that there are at least \( h \) other type \( G \) individuals in the market. Given the above probability, an individual deviating to a zero contribution level has an expected utility of

\[
E[U_{-d,i}|V,C,p,N,x_i = 0, h_{-i}] = V \cdot P_{h-1}.
\]

Expected utility for individual \( i \) when playing strategy \( h \) is given by Equation 3.1, with \( n = h \). For any given symmetric pure strategy \( h \), there is thus an incentive to deviate if

\[
V \cdot P_{h-1} > (V - \frac{C}{h}) \cdot P_h.
\]

After some math, there is thus a possible equilibrium if

\[
V \geq \frac{C}{h} \cdot \frac{P_h}{P_h - P_{h-1}}.
\]

The quantity \( P_h - P_{h-1} \) simplifies to the first term in the sum \( P_h \), and is hereafter referred to as \( P'_h \). The downward incentive constraint for deviating to a contribution level of zero is thus

\[
V \geq \frac{C}{h} \cdot \frac{P_h}{P'_h}, \quad (3.3)
\]

Only considering a deviation to a zero contribution level omits the possibility of a deviation equal to something less than \( \frac{C}{h} \). However, any downward deviation resulting in a positive contribution level is not incentive compatible.

**Lemma 2.** For any \( \{h|h \in \mathbb{Z} \cap \frac{C}{h} \leq h \leq \frac{(N-1)C}{C-V}\} \), the only incentive compatible downward deviation is to a contribution level of zero.

**Proof.** Consider a contribution of \( \epsilon \cdot \frac{C}{h} \), where \( \epsilon \in (0,1) \). Deviating down to a contribution level of \( \epsilon \cdot \frac{C}{h} \) necessitates that there be at least \( h \) other type \( G \) individuals in the market for successful funding, resulting in a probability of funding the public good of \( P_{h-1} \), equivalent to Equation 3.2.\(^{17}\)

\(^{17}\)A deviation contribution level of \( \epsilon \cdot \frac{C}{h} \) leaves \( C - \frac{C}{h} \cdot \epsilon \) of unfunded cost. This deviation then results in a necessary number of other contributors equal to \( h - \epsilon \). The probability of there being \( h - \epsilon \) other type \( G \) individuals in the
Expected utility for an individual $i$ deviating to $\epsilon \cdot \frac{C}{h}$ is then equal to

$$E[U_{-\epsilon,i}|V,C,p,N,x_i = \epsilon \cdot \frac{C}{h}, h_{-i}] = (V - \epsilon \cdot \frac{C}{h}) \cdot P_{h-1}.$$  

It is true then that expected utility from a deviation to a contribution of zero is greater than to any $\epsilon \cdot \frac{C}{h}$, or it is true that

$$(V) \cdot P_{h-1} > (V - \epsilon \cdot \frac{C}{h}) \cdot P_{h-1}. \quad \square$$

Lemma 2 permits as reasonable only a downward deviation to a contribution level of zero. Thus, the downward deviation constraint is the inequality Equation 3.3.

### 3.4.2 Upward Deviation Incentive Constraint

Similar to the case of downward deviations, possibilities for upward deviations from $h$ are uncountable. In order to identify incentive constraints for deviations in the upward direction, the analysis below uses a similar strategy as for the downward direction. First, incentive constraints are found for a subset of possible upward deviations, and then it is shown that this subset of possible upward deviations contain all reasonable deviations.

Consider an upward deviation from a contribution of $\frac{C}{h}$ to include an additional “share”, for a total contribution of $2 \cdot \frac{C}{h}$. If an individual $i$ of type $G$ deviates by a “share”, then the subjective probability of successfully funding the public good for individual $i$ is equal to

$$P_{h+1} = \sum_{k=h-2}^{N-1} \binom{N-1}{k} \cdot p^k \cdot (1-p)^{N-1-k},$$

or the probability that at least $h - 2$ other individuals in the market are of type $G$. Given the above probability, an individual $i$ deviating to an additional “share” contribution level has an expected utility of

$$E[U_{+1,i}|V,C,p,N,x_i = 2 \cdot \frac{C}{h}, h_{-i}] = (V + 2 \cdot \frac{C}{h}) \cdot P_{h+1}. \quad \text{market is equivalent to there being } h \text{ individuals, due to the fact that it is impossible to have a fraction of a type } G \text{ individual.}$$
For any given symmetric pure strategy \( h \), there is thus an incentive to deviate if

\[
(V + 2 \cdot \frac{C}{h}) \cdot P_{h+1} > (V - \frac{C}{h}) \cdot P_h.
\]

After some math, this leads to an incentive constraint given as

\[
V \leq \frac{C}{h} + \frac{C}{h} \cdot \frac{P_{h+1}}{P'_{h+1}},
\]

where \( P'_{h+1} \) has a definition analogous to \( P'_h \).

The above incentive constraint is in reference to the possible upward deviation of a single “share”. The same constraint with regards to a deviation of two “shares” is given as

\[
V \leq 2 \cdot \frac{C}{h} + \frac{C}{h} \cdot \frac{P_{h+2}}{P'_{h+2}}.
\]

There is no assurance that if Equation 3.4 holds it must be the case that Equation 3.5 holds. When considering all possible upward deviations of contribution “shares”, the upward deviation constraint is given as\(^{18}\)

\[
V \leq \min_{\forall \{d|d \in \mathbb{Z}, 1 \leq d \leq \frac{V_{s \cdot h}}{C}\}} \left\{ \frac{d \cdot C}{h} + \frac{C}{h} \cdot \frac{P_{h+d}}{P'_{h+d}} \right\}.
\]

The above incentive constraint doesn’t consider upward deviations of non-integer multiples of \( \frac{C}{h} \). The following lemma shows that the only reasonable upward deviations are integer multiples of \( \frac{C}{h} \), or deviations by full “shares”.

**Lemma 3.** For any \( \{h|h \in \mathbb{Z} \cap \frac{C}{h} \leq h \leq \frac{(N-1) \cdot C}{(N+1) \cdot h} \} \), the only incentive compatible upward deviations are by full “shares”, or integer multiples of \( \frac{C}{h} \).

**Proof.** Consider upward deviations of \( d \cdot \frac{C}{h} \) and \((d + \epsilon) \cdot \frac{C}{h}\), where \( \{d|d \in \mathbb{Z}, 1 \leq d \leq \frac{V_{s \cdot h}}{C}\} \), and \( \epsilon \in (0,1) \). An upward deviation of \( d \cdot \frac{C}{h} \) necessitates that there be at least \( h - 1 - d \) other individuals of type \( G \) in the market, resulting in a subjective probability of successful public good funding equal

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\(^{18}\) The maximum number of “shares” with which an individual will deviate upwards is equal to \( \frac{V_{s \cdot h}}{C} \) because contributing any more would imply a contribution level greater than \( V \) with some positive probability.
to

\[ P_{h+d} = \sum_{k=0}^{N-1} \binom{N-1}{k} \cdot p^k \cdot (1-p)^{N-1-k}. \]

An upward deviation of \((d+\epsilon) \cdot \frac{C}{h}\) also necessitates that there be at least \(h-1-d\) other individuals of type \(G\) in the market.\(^{19}\) Thus, \(P_{h+d+\epsilon} = P_{h+d}\), and it must be the case that

\[ (V - d \cdot \frac{C}{h}) \cdot P_{h+d} > (V - (d+\epsilon) \cdot \frac{C}{h}) \cdot P_{h+d}, \]

or, that the expected utility of upward deviation by some integer multiple of a “share” is always greater than a deviation by a “share” plus some \(\epsilon\).

\[ \square \]

Lemma 3 leaves only integer multiples of \(\frac{C}{h}\) as reasonable upward deviations. Thus the overall upward deviation incentive constraint is given as Equation 3.6.

### 3.4.3 Refinement of Equilibria

The downward and upward deviation constraints combine to form the overall individual incentive constraint

\[ \frac{C}{h^*} \cdot \frac{P_{h^*}}{P_{h^*}} \leq V \leq \min_{\forall d \in \mathbb{Z}, 1 \leq d \leq \frac{V}{h^*}} \left\{ d \cdot \frac{C}{h^*} + \frac{C}{h^*} \cdot \frac{P_{h^*+d}}{P_{h^*+d}} \right\}. \tag{3.7} \]

This overall individual incentive constraint of the subscription game results in a set of symmetric BNE values, \(h^*\). This set of equilibrium values is

\[ \mathbf{H} = \{ h^* | h^* \in \mathbb{Z} \cap \frac{C}{h^*} \cdot \frac{P_{h^*}}{P_{h^*}} \leq V \leq \min_{\forall d \in \mathbb{Z}, 1 \leq d \leq \frac{V}{h^*}} \left( d \cdot \frac{C}{h^*} + \frac{C}{h^*} \cdot \frac{P_{h^*+d}}{P_{h^*+d}} \right) \}. \]

The set of symmetric BNE of the contribution stage given above can be uniquely Pareto-ranked.

Figure 11 displays a graph of expected utility resulting from symmetric strategies \(h\) for particular

\(^{19}\)An upward deviation of \(d \cdot \frac{C}{h}\) leaves \(C - (d+1) \cdot \frac{C}{h}\) of unfunded cost. Dividing this into the “share” amount, or the amount that other individuals of type \(G\) will contribute at equilibrium, results in a necessary number of other contributers equal to \((h-d-1)\). An upward deviation of \((d+\epsilon) \cdot \frac{C}{h}\) leaves \(C - (d+1+\epsilon) \cdot \frac{C}{h}\) of unfunded cost. After similar math to above, this results in a necessary number of other type \(G\) individuals equal to \((h-d-1-\epsilon)\). The probabilities of there being \((h-d-1)\) and \((h-d-1-\epsilon)\) other type \(G\) individuals are equivalent due to the fact that it is impossible to have a fraction of an individual of type \(G\).
primal values and $C$. The shaded area in the graph represents the coverage of $H$, which in this particular case equals a minimum number of individuals of type $G$ necessary to fund the public good ranging from 107 to 110. In this specific case, the $h^* \in H$ can obviously be Pareto ranked, with $h^* = 107$ being the Pareto dominant equilibrium. A set $H$ can be uniquely Pareto ranked if the coverage of $H$ doesn’t include the maximum of the expected utility for all possible $h$. In fact, any set $H$ won’t include an $h^*$ to the left of the maximum expected utility value. To see this, note that for any $h$ to the left of the maximum expected utility, it must be the case that

$$(V - \frac{C}{h}) \cdot P_h < (V - \frac{C}{h+1}) \cdot P_{h+1},$$

or, that expected utility increases with $h$. However, it must also be true for any $h^* \in H$ that

$$(V - \frac{C}{h^*}) \cdot P_{h^*} \geq V \cdot P_{h^*+1},$$

which is simply the downward deviation individual incentive constraint. For both of the above equations to be true, it then must be that

$$V \cdot P_{h^*+1} < (V - \frac{C}{h^*+1}) \cdot P_{h^*+1},$$

which is impossible. Thus, the set $H$ is uniquely Pareto-ranked.

An intuitive way of refining the symmetric BNE is to consider the Pareto dominant equilibrium as a strategic focal point for contributors, and then assume that the only relevant equilibrium is the Pareto dominant one. This is equivalent to assuming a prior belief on the part of a contributor that all other contributors will select an $h^*$ corresponding to the Pareto dominant equilibrium with a probability of one, or that there is zero uncertainty in the “selection” of an equilibrium by other contributors. Refinement to the unique Pareto dominant symmetric BNE results in an $h^* = \min \{H\}$. Note that refinement to the Pareto dominant equilibrium necessarily omits consideration of the null set.\(^{21}\)

\(^{20}\)The primal values are $N = 200$, $V = 100$, $p = 0.50$, and $C = 2000$

\(^{21}\)Pareto dominance is equivalent to the concept of payoff dominance first put forth as a potential equilibrium selection method by Harsanyi et al. (1988). Much work has been done on equilibrium selection since then, including Harsanyi (1995), in which this type of selection method is found to be lacking. More recent equilibrium selection methods are not feasible given the setup of the subscription game in this paper. Included in the appendix is a section containing efficiency results for an equilibrium selection of $\max \{H\}$ as opposed to $\min \{H\} = h^*$. The qualitative
There is no closed form solution for the elements in any $H$. This paper uses an analytical technique for computing the $h^e$ coinciding with different primal values. The section on analytical calculation below contains an explanation of how this is done.

### 3.5 Monopoly Provider Equilibrium Analysis

The monopoly provider announces the posted cost of the public good, or $C_m$, in the posting stage of the subscription game. By assumption, the monopoly provider is a profit maximizing, risk-neutral agent. The subjective probability of successful public good funding for the monopoly provider is equal to

$$P_m = \sum_{k=h^e(C_m)}^{N} \binom{N}{k} \cdot p^k \cdot (1-p)^{N-k},$$

which is the probability that there are at least $h^e(C_m)$ individuals of type $G$ in the market. Expected profit for the monopoly provider is

$$\Pi = \left( F(C_m) \cdot \frac{C_m}{h^e(C_m)} - C_t \right) \cdot P_m(C_m),$$

where $F$ represents the expected number of individuals of type $G$ conditional on there being at least $h^e$ individuals, or

$$F = \frac{\sum_{k=h^e(C_m)}^{N} \binom{N}{k} \cdot p^k \cdot (1-p)^{N-k} \cdot k}{\sum_{k=h^e(C_m)}^{N} \binom{N}{k} \cdot p^k \cdot (1-p)^{N-k}}.$$

The objective on the part of the monopoly provider is then to

$$\max_{C_m} \Pi.$$

The trade off for the monopoly provider in increasing $C_m$ is between greater revenues conditional on successful public good funding and decreasing the probability of funding.

Similar to the case in the contribution stage, there is no closed form solution to this maximization problem. The solution to this maximization problem depends on the primal values $N$, $p$, results of this paper are robust to consideration of this symmetric BNE. The hope is that this comparison allays concerns about the equilibrium selection method used for the main results in this paper.
$C_t$, $V$, and the expected equilibrium behavior of type $G$ individuals in the contribution stage of the game. Equilibrium values $C_m^e$ are computed analytically for the results section of this paper.

### 3.6 Efficiency of the Subscription Game

The main purpose of this paper is to analyze the efficiency of the contribution game for differing primal values and provider types. It is natural to consider an outcome of the subscription game as ex post efficient if the public good is supplied when the aggregate willingness to pay for that public good meets or exceeds the true cost of supplying the good. Ex ante efficiency is then defined as the probability that the provider supplies the public good conditional on there being aggregate willingness to pay for the public good greater than or equal to the true cost. This probability is

$$P_{eff} = \sum_{a=0}^{N} \binom{N}{a} \cdot p^a \cdot (1 - p)^{N-a} \cdot \sum_{b=0}^{N} \binom{N}{b} \cdot p^b \cdot (1 - p)^{N-b}.$$

For the subscription game to be ex ante efficient, it must be the case that $h^e = \frac{C_t}{V}$, or that equilibrium individual contribution amounts are equal to $V$. This is only the case when $C_t = N \cdot V$. This special case of ex ante efficiency isn’t considered in the analysis of this paper. As discussed earlier, there is thus no expectation that the subscription game of this paper is ex ante efficient when considering a benevolent or monopoly provider.

### 3.7 Analytic Calculation of Equilibrium $C_m$ and $h$

As noted in the previous sections, the identification of $C_m^e$ and $h^e$ don’t allow for closed form solutions. In order to analyze ex ante efficiency of the subscription game in the presence of benevolent and monopoly providers of the public good, an analytic technique is employed. The subscription game is solved first for the contribution stage, and then for the posting stage.

For every $C \leq N \cdot V$, possible equilibrium values for $h$ are found by searching over all $h \in \mathbb{Z}[\frac{C_t}{V}, (N - 1) \cdot \frac{C_t}{V}]$ for $h^*$ that satisfy Equation 3.7. Pareto dominant refinement of these equilib-
rium values results in a unique $h^e$ for each $C$. If considering the outcome resulting from a benevolent provider, the posted cost is set as the true cost, or $C = C_t$, and efficiency results are computed. If considering the outcome resulting from a monopoly provider, profit levels are determined for every $C$, conditional on the $h^e$ corresponding to that $C$, and an equilibrium value $C^e_m$ corresponding to maximum profits is found.\textsuperscript{22} Ex ante efficiency, or $P_{eff}$, is then calculated using the equilibrium results obtained for benevolent and monopoly providers.

Equilibrium values and efficiency are dependent on $N$, $p$, $C_t$, and $V$. Thus, values for $C^e_m$, $h^e$, and $P_{eff}$ are calculated for differing primal values. Specifically investigated are changes in the true cost of providing the public good, or $C_t$, changes in the market size, or $N$, and changes in the scale, or equal proportional changes in $N$ and $C_t$, holding all else constant.

### 3.8 Equilibrium Results

In order to obtain results, a set of baseline primal values is assumed, and then equilibria are calculated for changes in certain primal values, holding all others constant. The baseline primal values are equal to $V = 100$, $N = 200$, $C_t = 2000$, and $p = 0.50$.

#### 3.8.1 Pareto Dominant Equilibrium Analysis

Analysis of efficiency and equilibrium allowing the true cost of the public good to vary is a logical place to start as the results with regards to a benevolent provider will provide expectations for contributor behavior as a monopoly provider varies the posted public good cost. Figure 12 presents graphical analysis of efficiency allowing the true public cost to vary, while holding all other primal values constant at baseline levels. As previously discussed, the contribution game is never ex ante efficient within analyzed ranges. Focusing on the benevolent provider curve in Figure 12a shows that as the true cost of the public good increases, the efficiency of the contribution game, or $P_{eff}$, will necessarily decline or remain the same.\textsuperscript{23} Consider a downward deviation constraint consistent with some $h^e$ and $C_t$. An increase in $C_t$ holding $h^e$ constant would increase the downward deviation constraint, potentially by enough such that Equation 3.7 no longer holds. In response, $h^e$

\textsuperscript{22}Allowing for changes in $C$ only as small as a dollar.
\textsuperscript{23}$P_{eff}$ may not decrease for small changes in $C_t$ due to the discrete nature of the binomial distribution.
must also increase in order that Equation 3.7 is again true. Intuitively, an increase in \( C_t \) increases the benefit of deviating to a contribution level of zero for a fixed \( h^c \), as each individual of type \( G \) is now contributing more than previously. This incentive to deviate must be reduced in order to reach a new \( h^c \). As Figure 13a shows, the minimum number of individuals of type \( G \), or \( h^c \), increases with \( C_t \). Contribution levels per contributor also increase with \( C_t \), as shown in Figure 13c, but not by enough to make up for the increased public good cost.

Figure 12a also shows that the efficiency of the contribution game is lower with a monopoly provider for any \( C_t \). The monopoly provider is willing to trade off probability of successful funding for increases in expected aggregate contributions until the decrease in probability from increasing the cost by an additional dollar is equal to increased contributions from the same. Figure 13b shows that the monopoly provider will increase the posted public good cost as the true cost increases. At high efficiency levels, and thus high overall probability of successful funding, there is more room for the monopoly provider to make these trade offs, resulting in an absolute loss of efficiency due to a monopoly provider that is greater the more ex ante efficient the subscription game with a benevolent provider. Figure 12b shows that relative efficiency losses fluctuate around a value of approximately 0.45, meaning that the subscription game with a monopoly provider is approximately half as efficient as that with a benevolent provider on average.\(^{24}\) It is shown below that this relative efficiency level is robust across the various analyses.

Figure 14 presents graphical analysis of efficiency allowing market size to vary, while holding all other primal values constant. Graph 14a plots \( P_{eff} \) for different values of \( N \). Focusing first on the results of a benevolent provider, efficiency increases with \( N \). Efficiency increasing with market size is in agreement with empirical results stemming from laboratory experiments on market size in subscription type games.\(^{25}\) Consider an increase in \( N \) while keeping some \( h^c \) constant at previous equilibrium levels. Unlike the case with increasing \( C_t \), an increase in \( N \) doesn’t affect the benefits of deviating to zero as the contribution level at the previous \( h^c \) remains the same. However, individuals of type \( G \) become more atomistic as \( N \) increases, thus decreasing the cost of deviating to a zero contribution. It is thus required that \( h^c \) increases as \( N \) increases. The new \( h^c \) could theoretically

\(^{24}\)The lumpiness in all efficiency and equilibrium results are due to the discrete nature of jumps in probability inherent in the binomial distribution.

\(^{25}\)See Isaac et al. (1994), Rondeau et al. (1999), and Rose et al. (2002) for examples.
result in more or less efficiency, although for the primal values analyzed in this paper efficiency increases with $N$.\textsuperscript{26}

Efficiency in the case of the monopoly provider is consistently lower than with a benevolent provider. The monopoly provider chooses a posted public good cost higher than the true cost for the same reasons as previously explained. Absolute efficiency losses are again greater for higher overall efficiency levels. Figure 14b graphs the relative efficiencies of a benevolent provider and monopoly provider. This relative efficiency fluctuates around a value of 0.44, meaning that a monopoly provider reduces the efficiency of the contribution game by about a half in comparison to a benevolent provider. This loss in relative efficiency is similar to losses with different variation choices.

Lastly, ex ante efficiency is analyzed for differing project scale levels holding all other primal values constant. The definition of project scale is some common multiple of $N$ and $C_t$ away from baseline values. The baseline values for $N$ and $C_t$ are 200 and 2,000 respectively, and thus a project scale of 2 would indicate $N = 400$ and $C_t = 4,000$. Increases in project scale increase the market size and the true cost of the public good while holding the individual value that contributors have over the public good constant. Figure 16a presents efficiency results for benevolent and monopoly providers. Efficiency decreases with increased project scale for both provider types. Increasing public good scale combines the affects from changes in $C_t$ and $N$. Thus, the benefit of deviating to zero increases and the cost of the same decreases with greater public good scale. These are disappointing results for the viability of the voluntary provision of expansive public goods. Efficiency with a monopoly provider is less than with a benevolent one. The absolute loss in efficiency is again greater for higher overall efficiency. Figure 16b shows relative efficiency levels are similar to the analyses when changing $N$ or $C_t$ individually, with $P_{eff}$ seemingly approaching a value of around 0.43 as scale increases.

\textsuperscript{26}Equilibrium efficiency values also generally increase for very large values of $N$. For example, $P_{eff} = 97.29$ at baseline primal values and $N = 100,000$, while if $N = 1,000,000$, then $P_{eff} = 99.28$. 

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3.9 Conclusion

In agreement with laboratory experiments and theory of contribution games similar to the game presented in this paper, efficiency increase as market size increases, and decreases as the cost of a public good increases. Interestingly, efficiency decreases as the scale of a public good increases. This suggests that the viability of voluntary provision of discrete public goods when there is incomplete information about potential contributor valuation is limited to small cost, localized public goods. In practice, many attempts to raise funds from voluntary contributors for the provision of a discrete public good will include other incentives for contributors such as rewards, raffles, etc. The results on low ex ante efficiency of successful public good funding with large scale goods highlights the potential importance of these secondary incentives.

The presence of a monopoly provider reduces the ex ante efficiency of successful public good funding. This is due to the fact that the monopoly provider has an incentive to trade off the probability of successful funding for increased aggregate contributions conditional on successful funding. The relative efficiency levels are stable across different parameter considerations, with a monopoly provider being approximately half as likely to supply the public good as a benevolent provider. Competition levels in markets for public good provision are an important determinant of ex ante efficiency if the provider can be considered a profit maximizing entity.

The contribution game presented in this paper is made relatively simple through assumptions in order to allow for easy calculation of ex ante efficiency. Enriching the model through additional components and reductions in assumptions would allow for the model to more closely approximate reality. For example, it may be worthwhile to change draws over valuation for the public good from a Bernoulli distribution to some continuous one. This assumption may more closely approximate actual valuation over a population for many discrete public goods. Also, including additional providers of similar, but non-identical, public goods may allow for analysis that more closely approximates a reality of some form of competition amongst public good providers.
Appendices
Appendix A  Alternative Equilibrium Comparison

The following short analysis compares the main ex ante efficiency results of this paper to results assuming that $h^e = \max\{H\}$.

Figure 18 presents graphs representing efficiency results for $h^e = \max\{H\}$ and allowing $C_t$ to vary. Comparing these results to Figure 12 shows very little difference between the two. Efficiency levels start at a slightly lower level and fall faster towards approximately zero in Figure 18a. Also, as shown in Figure 18b, when efficiency levels fall to approximately zero, a monopoly provider will set a posted cost equal to the true cost under the alternative equilibrium.

Figure 19 presents graphs representing efficiency results for $h^e = \max\{H\}$ and allowing $N$ to vary. There are almost no discernible differences between Figure 19 and Figure 14 other than the fact that, again, at approximately zero efficiency levels the monopoly provider will post a public good cost equal to the true cost under the alternative equilibrium.

Figure 20 presents graphs representing efficiency results for $h^e = \max\{H\}$ and allowing public good scale to vary. Efficiency levels are everywhere lower for a particular scale under the alternative equilibrium. In the case of the benevolent provider, efficiency is approximately halved when comparing Figure 20a to Figure 16a. Efficiency decreases with increasing scale under both equilibrium considerations, thus preserving the results of the dynamics of project scale across both. Relative efficiency between a benevolent and monopoly provider is everywhere greater under the alternative equilibrium. However, the range of relative efficiency values in both cases are roughly in line with the results in the rest of the paper.
Appendix B  Tables
Table 1: Literature Review Summary

<table>
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<tr>
<th>Unit of Obs</th>
<th>Risk Measure</th>
<th>Time Frame</th>
<th>Methodology</th>
<th>Ceteris Paribus</th>
<th>Result</th>
<th>Overall</th>
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<tr>
<td>Liang and Rhoades (1988)</td>
<td>High Holder Earnings and Equity</td>
<td>1976-1985</td>
<td>Event Study OLS</td>
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<td>1994</td>
<td>AIDS (structural)</td>
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<td>Ricard and Thomas (1997)</td>
<td>BHC Earnings</td>
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<td>Recursive Model (OLS)</td>
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<td>Carlson (2004)</td>
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<td>1929-1933</td>
<td>Logit</td>
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<td>Glantz et al. (2014)</td>
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<td>1986-2007</td>
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<td>0.060</td>
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### Table 3: Main Logit Regression Results

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<th>95% C.I.</th>
<th>Coefficient</th>
<th>Marginal Effect</th>
<th>95% C.I.</th>
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<td>0.055***</td>
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<td>0.015</td>
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<td>0.063***</td>
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<td>0.065***</td>
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<table>
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<tr>
<td>obs</td>
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<td>32478</td>
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*a* Marginal effects are average marginal effects.

*b* Confidence intervals are with respect to average marginal effects.

*c* * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.
Table 4: Correlations and OLS Regression Results, Diversity Measure and Explanatory Variables

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<td>Correlation</td>
<td>OLS Regression</td>
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Obs: 101080 32221

* denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.
Table 5: Fitted Probabilities

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<td>0.5 ≥ diverse &lt; 0.6</td>
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## Table 6: Disposition of Projects at End of Funding Period, by Genre

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<td>Art</td>
<td>66</td>
<td>32</td>
<td>34</td>
<td>51.5</td>
</tr>
<tr>
<td>Fashion</td>
<td>64</td>
<td>43</td>
<td>21</td>
<td>32.8</td>
</tr>
<tr>
<td>Comics</td>
<td>52</td>
<td>17</td>
<td>35</td>
<td>67.3</td>
</tr>
<tr>
<td>Photography</td>
<td>40</td>
<td>21</td>
<td>19</td>
<td>47.5</td>
</tr>
<tr>
<td>All Others</td>
<td>74</td>
<td>28</td>
<td>46</td>
<td>62.2</td>
</tr>
</tbody>
</table>

All Others includes the genres crafts, theater, dance, and journalism.
Table 7: Summary Statistics of Project Characteristic Variables, by Project Success

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Projects</th>
<th>Unsuccessful Projects</th>
<th>Successful Projects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.d.</td>
<td>Mean</td>
</tr>
<tr>
<td>Goal</td>
<td>13817</td>
<td>23176</td>
<td>17172</td>
</tr>
<tr>
<td># of Videos</td>
<td>0.248</td>
<td>0.924</td>
<td>0.196</td>
</tr>
<tr>
<td># of Images</td>
<td>7.384</td>
<td>9.904</td>
<td>6.014</td>
</tr>
<tr>
<td>Words in Description</td>
<td>710</td>
<td>606</td>
<td>627</td>
</tr>
<tr>
<td>Observations</td>
<td>1136</td>
<td></td>
<td>581</td>
</tr>
</tbody>
</table>
## Table 8: Summary Statistics, Dynamic Variables of Interest in Logit Regressions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.d.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>sharesper</td>
<td>0.180</td>
<td>4.835</td>
<td>0</td>
<td>493</td>
</tr>
<tr>
<td>backersper</td>
<td>0.036</td>
<td>0.932</td>
<td>0</td>
<td>90</td>
</tr>
<tr>
<td>fundingleft</td>
<td>12017</td>
<td>22143</td>
<td>1</td>
<td>238299</td>
</tr>
</tbody>
</table>

Observations 27731
Table 9: Reduced Form Model Results

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Funding Fixed Effect Regression</th>
<th>Funders Fixed Effect Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>95% C.I.</td>
</tr>
<tr>
<td>probeffect</td>
<td>59.022</td>
<td>-1.139</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>newbackers</td>
<td>55.481</td>
<td>24.419</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>newshares</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>prevfunders</td>
<td>-3.503</td>
<td>-7.169</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.805)</td>
</tr>
<tr>
<td>prevraised</td>
<td>0.056</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.747)</td>
</tr>
<tr>
<td>prevshares</td>
<td>0.329</td>
<td>-0.180</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.144)</td>
</tr>
</tbody>
</table>

Observations       | 32944       | 32944

Project and day fixed effects included in both models.
Day of week controls included in both models.
Panel regression standard errors clustered along project dimension.

*** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.
P-values in parentheses.
Appendix C  Figures
Figure 1: Risk-Reward Frontier
Figure 2: Heat Maps for U.S. Commercial Bank Failures

(a) 1985-1992

(b) 2008-2013
Figure 3: Analysis of Average Marginal Effects of *diverse* on Probability of Insolvency, by *diverse* Level

(a) Histogram of *diverse* Levels, 1985-1992

(b) Average Marginal Effects of *diverse* on Probability of Insolvency, by *diverse* Level

(c) Histogram of *diverse* Levels, 2008-2013
Figure 4: Histogram of Difference Between Final Amount Raised and Goal
Figure 5: Mean Daily Funding in Dollars, by Day in Funding Period
Figure 6: Mean Daily Funders Added, by Day in Funding Period
Figure 7: Ratio of Mean Daily Funding to Mean Daily Funders, by Day in Funding Period
Figure 8: Mean Daily Values, Logit Specification Variables of Interest

(a) Mean Values for $shares_{per}$, by Day in Project Duration

(b) Mean Values for $backers_{per}$, by Day in Project Duration

(c) Mean Values for $funding_{left}$, by Day in Project Duration

Mean values include days 2 – 30 for all projects yet to be fully funded at the start of the day.
Figure 9: Graphs of Logit Results for *sharesper* and *backersper*

(a) Average Semi-Elasticity of *sharesper* on Probability of Project Success by Day

(b) Average Semi-Elasticity of *backersper* on Probability of Project Success by Day

Dependent variable is ultimate success of project funding. Results from running separate logits for days 2 – 30.
Figure 10: Graphs of Effect Proxy Variable by Day

(a) Value for $probeffect$ by Day, All Projects

(b) Value for $probeffect$ by Day, Excluding Projects Already Successfully Funded
Figure 11

Expected Utility from Symmetric Strategy $h$

- **Coverage of Nash Equilibria**
- **Expected Utility**
Results allow the true public good cost, $C_t$, to vary while holding other primals constant at baseline values. Baseline values are $N = 200$, $V_s = 100$, and $p = 0.50$. 
Results allow the true public good cost, $C_t$, to vary while holding other primals constant at baseline values. Baseline values are $N = 200$, $V_s = 100$, and $p = 0.50$. 

Figure 13: Graphs of Equilibrium Values, Varying True Public Good Cost ($C_t$)
Results allow the market size, $N$, to vary while holding other primals constant at baseline values. Baseline values are $C_t = 2000$, $V_s = 100$, and $p = 0.50$. 
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Results allow the true public good cost and market size, $C_t$ and $N$, to vary proportionally while holding other primals constant at baseline values. Baseline values are $V_s = 100$, and $p = 0.50$. 
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Results allow the true public good cost, $C_t$, to vary while holding other primals constant at baseline values. Baseline values are $N = 200$, $V_s = 100$, and $p = 0.50$. 
Figure 19: Graphs of Efficiency Results, Alternative Equilibrium, Varying Market Size (N)

Results allow the market size, \( N \), to vary while holding other primals constant at baseline values. Baseline values are \( C_t = 2000, V_s = 100, \) and \( p = 0.50 \).
Results allow the true public good cost and market size, $C_t$ and $N$, to vary proportionally while holding other primals constant at baseline values. Baseline values are $V_s = 100$, and $p = 0.50$. 
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