Technology Adoption in Input-Output Networks

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Abstract

This paper studies how network structure can affect the speed of adoption. In particular, we model the decisions to adopt Python 3 by software packages. Python 3 provides advanced features but is *not* backward compatible with Python 2, which implies adoption costs. Moreover, packages form input-output networks through dependency relationship with other packages, and they face additional adoption cost if the dependency packages lack Python 3 support. We build a dynamic model of technology adoption that incorporates such a network, and estimate it using a complete dataset of Python package. Estimation results show the average cost of one incompatible dependency is roughly three times the cost to update one's own code. We conduct counterfactual policies of community-level targeted cost subsidy and show network structure is crucial to determine an optimal policy of cost subsidy.

1 Introduction

> *If one examines the history of the diffusion of many inventions, one cannot help being struck by two characteristics of the diffusion process: its apparent overall slowness on the one hand and the wide variations in the rates of acceptance of different inventions on the other.*
>
> – Rosenberg (1972)

Technological innovation has been one of the most important sources of productivity and economic growth (DeLong (2002), Mansfield, Mettler, and Packard (1980)), yet slow technology adoption is still a common phenomenon in many sectors (Geroski (2000)). The rich literature of technology adoption shows many factors can slow down the speed of adoption: for example, organization (Atkin et al. (2017)), competition (Gowrisankaran and Stavins (2004)), and network effects (Saloner and Shepard (1995)).[1] This paper contributes to the literature by demonstrating another channel through which the speed of adoption can be affected—namely, input-output networks.

As the economy becomes more disaggregated, firms specialize in one specific type of product or service and form input-output networks.[2] Specialization generates efficiency gains but linkages between firms may have adverse effects on new technology adoption (Katz and Shapiro (1985)). For example, wireless carriers are unable to adopt 5G technology without 5G equipment from suppliers. If suppliers experience negative shocks or are pessimistic about the new technology, buyers' adoption decisions are also affected and the industry-level 5G adoption may stall.[3]

This paper investigates how network structure affects individual technology adoption decisions in a dynamic setting. We study this issue in the context of the Python programming language, in particular, the transition from Python version 2 to version 3.[4] Python is one of the most popular programming languages in the world. Python 3 was a major release in 2008 that experienced slow adoption.[5] Python 3 provides several fundamental improvements but is *incompatible* with Python 2.[6] In other words, existing code written in Python 2 often fails to work in Python 3, and vice versa.

Like other programming languages, most functionalities on Python are provided by third-party packages. Packages are also known as libraries, (sub)routines, or modules in other programming languages. These packages form input-output networks through dependency requirements: Downstream packages are built using functionalities provided by upstream packages, or upstream packages are dependencies for downstream packages.[7] To use a pack-

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[1]For more examples, refer to the excellent surveys by Atkin et al. (2017), Hall and Khan (2003), and Hall (2009)

[2]An input-output network is also known in other literature as a vertical or hierarchical network.

[3]Other examples of technology adoption in input-output networks include payment systems and industry 4.0.

[4]Similar issues exist in other software or programming languages, such as Windows DLLs, Fortran, and Ruby. We study Python mainly due to data availability.

[5]The Python 3 adoption process has been widely considered a slower-than-optimal process.

[6]Please refer to the Appendix for a list of new functionalities in Python 3 that are incompatible with Python 2.

[7]The two terms "upstream" and "dependency" are used interchangeably throughout the paper.

age, the end user must install the package itself, as well as all of its upstream dependencies.[8]

Our research focuses on the decisions to adopt Python 3 made by third-party packages. This adoption decision means updating the package to be compatible with Python 3. To use the new features of Python 3, packages need to update their source code. Moreover, another major component of the adoption costs comes from the incompatibility between Python 2 and 3. If one or more of their upstream dependencies have yet to adopt Python 3, additional development efforts must be made, i.e. higher adoption cost.[9]

Unlike other industries with input-output networks, there is no explicit pecuniary compensation in OSS development and usage. This particular feature allows us to focus on the pure impact of the network structure itself without the complication when price is introduced. We model the utility of OSS as a function of user downloads (Fershtman and Gandal (2011)). For any commonly-known motivations behind contributions to Open Source Software (OSS) (e.g., altruism, career incentives, ego gratification), more user downloads are always better for package developers.

To understand how network structure affects the dynamics of technology adoption, we build a dynamic model in which each package makes an irreversible decision to adopt Python 3, following Rust (1987) and Keane and Wolpin (1997). B. Our model highlights an intertemporal trade-off: If a package adopts early, it can receive more user downloads over time but pays a higher adoption cost; if a package adopts later, the adoption cost might be lower due to the future adoption decisions of its upstream dependencies.

The solution of the dynamic adoption model requires a prediction of future states for a package itself and for each of its dependencies, as well as those of the dependencies of dependencies, and so on.

Heterogeneity plays an important role in studying decisions to adopt a new technology (Ryan and Tucker (2011)).[10] Our model accounts for rich patterns of heterogeneity across individual agents. Apart from differences in individual characteristics, we consider the detailed linkages among packages and allow them to discount future utilities differently. By imposing a functional form, we also use several package characteristics that can potentially affect how package developers value future downloads to capture heterogeneity in the discount factor.

With a complete dataset of package characteristics, historical releases and user download statistics, we draw the input-output structure of packages.[11] We group packages into various layers based on the dependency relationship, and calculate the adoption probability layer by layer. Then we propose a novel maximum likelihood estimation (MLE) method to estimate model parameters.

Results from the structural estimation show that upstream dependencies without Python 3 support pose significant barriers in the adoption decisions of downstream packages: The

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[8]The installation system usually checks whether all dependencies have been installed, and if not, it automatically downloads and installs them first. Please see Section 2 for more information.

[9]Typical solutions (or costs) come from looking for alternative dependencies with Python 3 support, or updating the necessary components of the dependency in order to support Python 3.

[10]Ryan and Tucker (2011) studies a similar topic by measuring the heterogeneous network effects in adopting a videocalling technology within a company, but only at the employee-type level. Our paper incorporates a much richer level of heterogeneity at the individual-agent level.

[11]Our data come from the Python Package Index project, which is the largest repository for Python packages. It records historical download information for more than 150,000 packages from 2005 onward.

cost of adopting Python 3 with one dependency lacking Python 3 support is equivalent to, on average, three times the cost of updating one's own source code.

The structural model allows us to conduct counterfactual exercises of "sponsorship." A sponsor promotes the new technology, and can affect its future success (Katz and Shapiro (1986)). We evaluate the effectiveness of policies such as community-level targeted cost subsidy to adopt Python 3. Using modularity optimization tools developed in the social network literature, the packages are grouped into various "communities" based on the dependency network: for example, web development and data analysis communities. These communities differ significantly in their network structure. Packages are more densely linked within a community but less so across different communities. Through counterfactual simulation, we show how technology adoption decisions can progapate through these connected communities. Counterfactual results show that community-level targeted cost subsidies have large heterogeneous effects on adoption rates due to differences in network structure within a community. Moreover, subsidies in one community has significant *positive or negative* effects on connected communities. We also explore the optimal policy to maximize the effectiveness of cost subsidies to promote a faster Python 3 adoption. The findings imply policies that consider network structure can significantly improve the effectiveness of promotion.

This paper contributes to the empirical literature of networks and technology adoption decisions.[12] Previous papers of network effects/externalitiies study the topic using a more "reduced-form" approach by modeling utility as a function of the total number of users on the same network. Our research considers the detailed linkages between individual agents on a network. This paper also contributes to the literature of network analysis. Previous studies of networks mainly adopted static models, whereas in reality, individuals are inherently dynamic and face intertemporal tradeoffs. Failure to control for forward-looking agents can yield different estimation results and may misguide policymakers (Rust (1987), Hendel and Nevo (2006), Gowrisankaran and Rysman (2012)). This paper is among the first to link the literature of dynamic discrete choice models to network analysis. It also contributes to the literature of technology adoption by showing how input-output networks can lead to adverse effects on the technology adoption process in a dynamic setting.

2 Background: the Python Programming Language

Python is a general-purpose programming language.[13] It has a syntax that allows users to express concepts in fewer lines of code compared to most other major programming

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[12]Björkegren (2018) also studies technology adoption in a social network setting. He circumvents the complex problem by solving per-period equilibria of optimal timing to adopt, and assumes that each individual makes the adoption decision based on actual future adoption time of her contacts. Our approach uses the dynamic discrete choice model, which is more realistic and flexible: Individuals decide whether to adopt a new technology in the current time period, instead of when to adopt a new technology in a future time period; Agents are uncertain of others' adoption decisions, instead of having a perfect foresight of others' adoption decisions; The belief of others' adoption probability vary over time.

[13]A general-purpose programming language is a computer language that is broadly applicable across application domains. Examples of general-purpose programming languages include C, Java, and Python. It is in contrast to domain-specific language, such as MATLAB (numerical computing), Stata and R (statistical analysis), etc.

Growth of major programming languages
Based on Stack Overflow question views in World Bank high-income countries
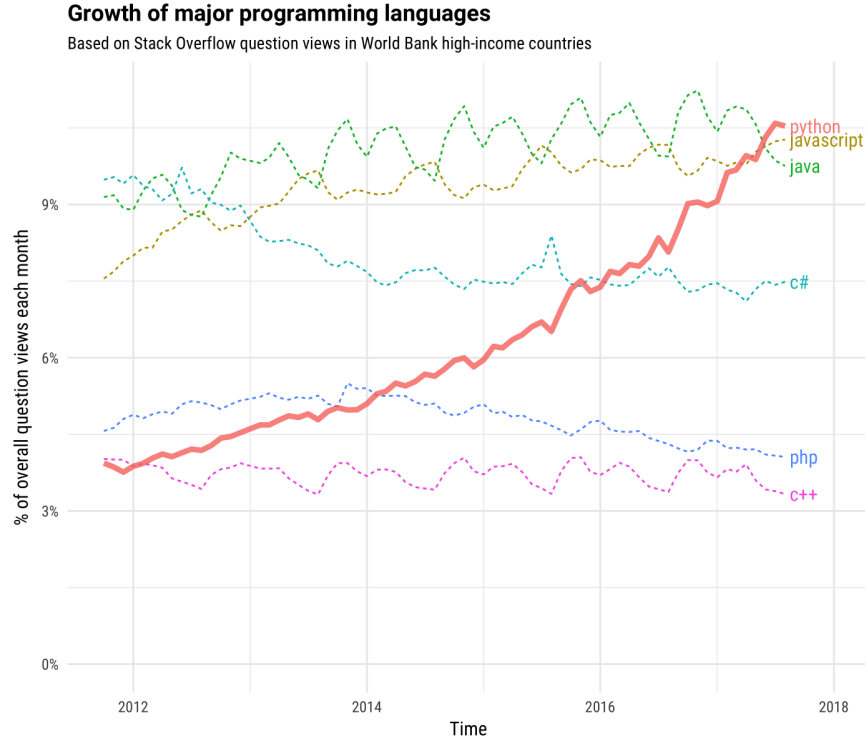
Figure 1: Popularity Trend of Programming Languages

languages, and has been widely used in introductory level computer science courses at universities. The first version was released in 1989 but did not gain popularity until the late 2000s. In the past few years, Python has become one of the most popular programming languages. Figure 1 plots the numbers of visits to questions related to a particular programming language on Stack Overflow, the largest Q&A website for programming-related matters. Python has grown to be the number one in 2018 based on this measure.

Backward compatibility has been a widely-disputed topic in the software industry. In order to introduce several key features to Python, the core developers decided to break the backward compatibility with the major release of Python 3 in 2008.[14] The tradeoff is clear: easier user transition to new technology vs. higher cost of development and slower innovation. Users and package developers who want to run their code on Python 3 have to update all the source code to be compatible with Python 3.[15]

Most functionalities on Python are provided by third-party packages. In simple terms, packages can be viewed as a collection of tools and functions that anyone can use to work

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[14]Python core developers are a group of active contributors to the Python programming language, which itself is an OSS. Some of the major new features of Python 3 include newer classes, Unicode encoding, and float division. Please refer to `http://python.org/` for more detailed information. Several examples of incompatibility are shown in the Appendix 9.1.

[15]Some packages are developed to help users to transit to Python 3 easier automatically. However, in most cases, users and package developers still have to test and manually modify much of code.
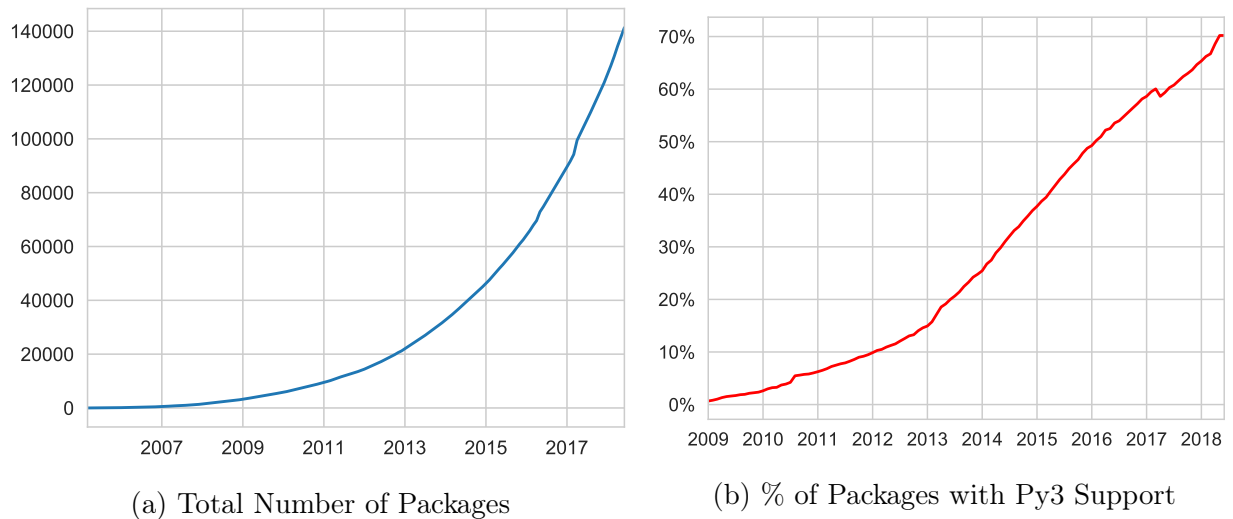
(a) Total Number of Packages

(b) % of Packages with Py3 Support

Figure 2: Python Packages with Python 3 Support

on more complicated tasks.[16] Packages are also known as libraries, modules, (sub)routines in other programming languages.

Figure 2.a plots the number of packages available on Python over time. The exponential growth of packages is another indication that Python itself has gained tremendous popularity over the past decade. Figure 2.b plots the percentages of packages with Python 3 support after its release in 2008. The transition process has been longer than many expected, and many packages are reluctant to provide Python 3 support. Those with Python 3 support usually provide two versions for each release: one for Python 2 and another for Python 3. By the end of 2018, roughly 82% of packages support Python 3.

Both the Python programming language and almost all the third-party packages are Open Source Software (OSS).[17] The motivations of OSS contribution by software developers can be multifold.[18] The literature of motivations behind private contributions to online public goods suggests that the most common motivations are altruism, career concerns, ego gratification, etc.

Packages usually specialize in a specific domain, and often depend on other packages for related functionalities. For example, *NumPy* is a package that specializes in certain fundamental mathematical operations such as matrix inversion and multiplication; *SciPy* provides more applied tools used in science, such as linear regression, which requres the the matrix operations from *NumPy*. In this case, *SciPy* depends on *NumPy*, or *NumPy* is a dependency of *SciPy*. To use *SciPy*, the user has to install both *NumPy* and *SciPy*. When installing a package, the system usually checks whether all the dependencies have been properly installed, and if not, it automatically downloads and installs the dependency

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[16] A more accurate description and definitions of packages can be found in the official Python documentation at `https://docs.python.org`. The Appendix 9.2 also provides a simple example to show one can do with packages.

[17] Nearly all the Python packages in our study are open source, which are free of charge to anyone to use. A limited number of packages offer free downloads but requires payment for usage.

[18] von Krogh et al. (2012) and Xu, Nian, and Cabral (2019) provide overviews of the literature.
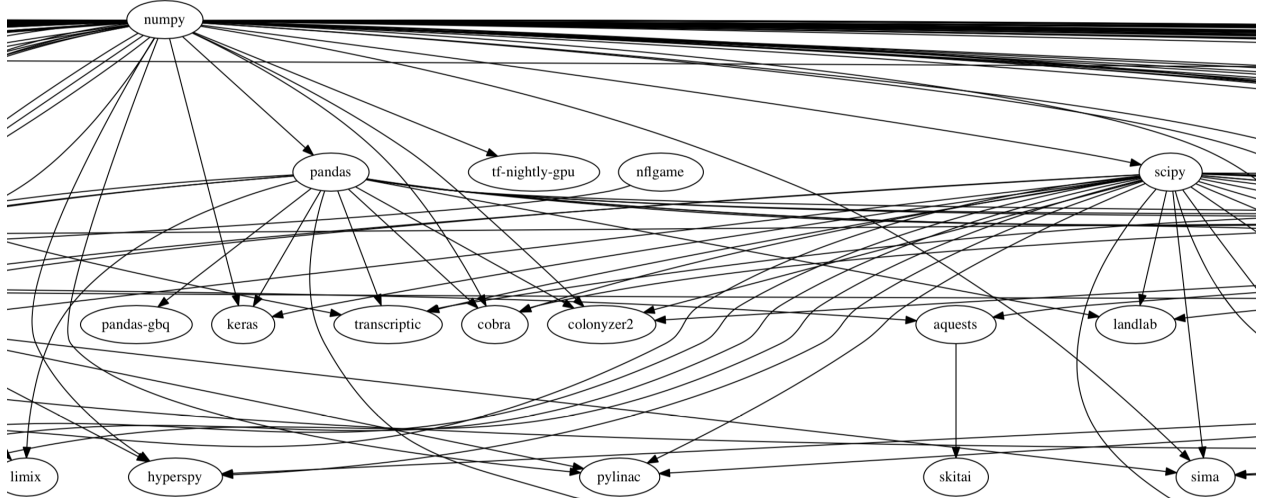
6

Figure 3: Sample Input-Output Network of Python Packages

packages first.

Figure 3 shows a small section of the input-output network of Python packages. The arrows represent the dependency relationship. For example, An arrow from *NumPy* to SciPy means *NumPy* is the dependency of *SciPy*.[19][20] In this case, we also refer to *NumPy* as the upstream package to the downstream package *SciPy*.

3   Data

We collect data from the Python Package Index (PyPI), a repository of software for the Python programming language. In other words, it is a website where all developers upload their packages so that users can search and download packages they need.

When uploading packages to PyPI, package developers usually provide various information related to the files, such as the description of the package, the contact information of owners, whether they provide support for Python 2 or Python 3, and what other packages are required as dependencies. Table 1 lists some basic information related to a package. The dependency requirement comes from the "requires_dist" section, and the Python 2/3 support status can be found in the "classifiers" section.[21]

User downloads data consists of two separate sources recorded by PyPI. Before 2016, cumulative download statistics for each file is recorded (Table 2.a). The system stopped working for a few months from January to May 2016, when PyPI introduced a new system

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[19]In principle, the whole input-output network is acyclic. In other words, circular dependency relationship such as $A \to B \to C \to A$ is not supposed to exist. In the data, there exist a small number of cases of circular dependencies. We compare the characteristics of all package pairs and manually remove the weakest link, measured by the number of times a package is used as a dependency.

[20]***add SciPy & NumPy

[21]In addition to the information provided by developers in the description section, we also infer Python 2/3 support from filenames and extract dependency requirements directly from the source files of each package.

Table 1: Package Characteristics

name	statsmodels
license	BSD
summary	Estimation and inference for statistical models
author	Josef Perktold, Chad Fulton, Kerby Shedden
version	0.9
requires_dist	numpy
	pandas
	matplotlib
classifiers	Intended Audience :: Science/Research
	Programming Language :: Python :: 2
	Programming Language :: Python :: 3
	Topic :: Scientific/Engineering

Table 2: Downloads Statistics

(a) Before 2016: Cumulative Download

upload_time	2014-12-02
python_version	3.4
downloads	41564
filename	statsmodels-0.6.whl
size (bytes)	3969880

(b) After 2016: Individual Download

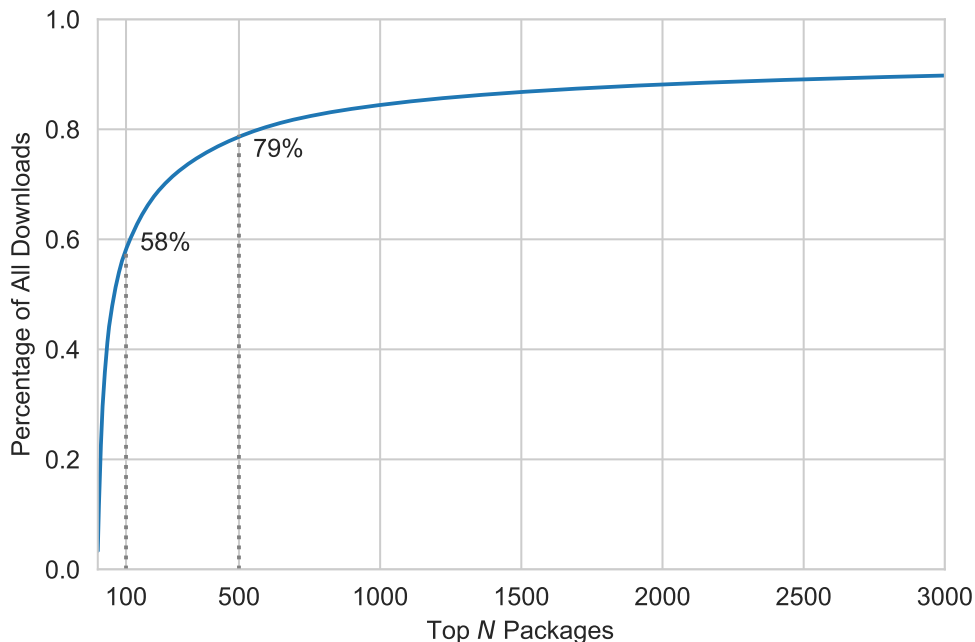|	
timestamp	2018-09-01
country_code	FR
filename	statsmodels-0.6.whl
project	statsmodels
version	0.6
python	3.4
system	Mac OS X

Figure 4: Total Downloads of Top Packages as Percentage of All Downloads

hosted on Google BigQuery.[22] The new system records and publishes certain information related to each individual download (Table 2.b). We combine the two sources of user downloads data and extrapolate the number of downloads for the missing time periods from January to May 2016.[23]

Among the more than 150,000 packages hosted on PyPI (as of September 2018), the vast majority are either abandoned or hobby projects for personal use. For example, 40% of all packages have only one or two releases. Figure 4 plots the total downloads of top N packages as a percentage of all downloads in 2017. It shows a long tail of downloads across packages: top 100 packages account for approximately 58% of all downloads and top 500 packages account for 79% of all downloads. The long tail is persistent throughout all the years.

We focus on packages that are well-maintained with regular releases by selecting packages based on the following criteria (values in parenthesis are the unconditional percentage of packages that satisfy each measure):

- Time Duration (Last Release - First Release Date) $\geq$ 1 Year (12.9%)

- Downloads per Year $\geq$ 2000 (30.8%)

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[22]Google BigQuery provides cloud-based data warehouse services. It can record a large amount of data in real time, and provides end users with easy access and manipulation of the stored data.

[23]Competing platforms to PyPI also exist (such as Anaconda). All packages on Anaconda are also hosted on PyPI. However, user downloads through Anaconda are not recorded. Throughout our data period, Anaconda holds a relatively small market share. Unfortunately, there is no publicly available information on the downloads statistics of packages hosted on Anaconda.

- Total Number of Releases ≥ 5 (38.9%)

- Total Releases / Time Duration ≥ 1 (92.4%)

- Some Python 2/3 Support Info Available (59.9%)

These selection criteria provide 3,397 packages for our analysis.

Table 3: Summary Statistics

	All	Selected	Selected with ≥ 1 Dependency
Number of packages	125521	3397	2143
Total downloads (in percentage)	100.00%	46.40%	22.32%
Average logged downloads per package	9.27	12.34	12.30
(min, max)	(3.0, 20.5)	(8.8, 20.5)	(8.8, 19.7)
Average number of dependencies	0.07	2.27	3.60
(min, max)	(0, 53)	(0, 53)	(1, 53)
Average logged package size (KB)	4.32	4.42	4.49
(min, max)	(-2.1, 11.2)	(-2.1, 11.2)	(-0.2, 9.7)

Table 3 shows the summary statistics of several key variables between the whole population and our selected sample. The selected sample includes the majority of the most popular packages on Python, consisting 51.69% of all of the downloads on PyPI. The average number of downloads for each package in the selected sample is also much higher than the whole population. On average, the selected sample has 3.12 dependencies vs. 0.72 in the whole population. These packages are also larger in terms of file sizes. Consistent with other figures in this section, Table 3 implies that our analysis focuses on the well-maintained packages with regular releases that faced a adoption decision of Python 3. These packages are also the most popular packages in the Python community.

4 Model

Our model is based on the single agent dynamic discrete choice framework developed by Rust (1987) and Keane and Wolpin (1997) to analyze technology adoption decisions by Python packages. Each package i at time t can be described by a state variable $S_{i,t}$. Given the current state $S_{i,t}$, each package i makes an irreversible decision to adopt Python 3, namely, to make the package compatible with Python 3.[24] Let $d_{i,t}$ be the a binary irreversible decision:[25]

$$d_{i,t} = \begin{cases} 1 & \text{if package } i \text{ adopts Python 3 at time } t \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

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[24]More examples of irreversible decisions as well as discussions can be found in Rust and Phelan (1997) and Aguirregabiria and Mira (2010).

[25]Given the irreversibility condition, we use $d_{i,t}$ to represent both the adoption decision and status, i.e. once a package adopts Python 3 at time t ($d_{i,t} = 1$), it always supports Python 3 in future periods ($d_{i,t+\tau} = 1 \quad \forall \tau \in N$)

Packages are linked through dependency requirements. In order to incorporate the dependency network of packages and how packages affect each other through their adoption decisions, the state variable includes both one's own characteristics as well as those of dependencies. Thus, the (nested) state variables can be specified as the following:

$$
S_{i,t} = \Big\{ \underbrace{x_{i,t-1}}_{\substack{\text{user} \\ \text{downloads}}}, \underbrace{z_{i,t}}_{\substack{\text{other package} \\ \text{characteristics}}}, \underbrace{\epsilon_{i,t}^{d_{i,t}}}_{\substack{\text{i.i.d.} \\ \text{shocks}}}, \underbrace{d_{i,t-1}}_{\substack{\text{previous} \\ \text{adoption decision}}}, \underbrace{\{S_{j,t}, d_{j,t}\}_{j \in U_{i,t}}}_{\substack{\text{states and decisions} \\ \text{of dependencies}}} \Big\}.
$$

The dependency network among packages is incorporated in the last component of the state variable. That is to say, the adoption decision of a package depends on the decisions and states of all of its dependencies as well as dependencies of dependencies, etc. One implicit assumption embedded in this nested state variable is a sequential move assumption, meaning package i observes the adoption decision made by its dependencies before making its own adoption decision. Section 4.3 provides more discussion and implications on this assumption.

All adoption decisions are irreversible, meaning that in each time period t, only packages without Python 3 support make the adoption decisions. The adoption decision comes with a one-time adoption cost, and this affects the transition dynamics of the state variable $S_{i,t}$.

4.1   Value Function and Bellman Equation

Given the state $S_{i,t}$, a package's flow utility can be written as:

$$
u(S_{i,t}, d_{i,t}; \theta) - C(S_{i,t}, d_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}} \tag{2}
$$

$$
= u(S_{i,t}, d_{i,t}; \theta) - \mathbf{1}(d_{i,t-1} = 0, d_{i,t} = 1) \, C(S_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}}, \tag{3}
$$

where $u(S_{i,t}, d_{i,t}; \theta)$ is the reward function of the indirect utility, and $C(S_{i,t}; \theta)$ is the one-time cost to adopt Python 3.

The value function for packages without Python 3 support can be written as the following dynamic problem:

$$
V_\theta(S_{i,t}, d_{i,t-1} = 0) \tag{4}
$$

$$
= \max_{\{d_{i,t+\tau}\}_{\tau=0}^\infty} \mathbf{E}_t \{ \sum_{\tau=0}^\infty \beta_i^\tau \Big(u(S_{i,t+\tau}, d_{i,t+\tau}; \theta) - D_{i,t+\tau} \, C(S_{i,t+\tau}; \theta) + \nu_{i,t+\tau}^{d_{i,t+\tau}} \Big) | S_{i,t}; \theta \}, \tag{5}
$$

$$
\text{where} \quad D_{i,t+\tau} = \mathbf{1}(d_{i,t+\tau-1} = 0, d_{i,t+\tau} = 1) \tag{6}
$$

The Bellman equation implies at each period t, the ex ante value function, conditional on $d_{i,t-1} = 0$, can be represented by:

$$
V_\theta(S_{i,t}, d_{i,t-1} = 0) \tag{7}
$$

$$
= \max_{d_{i,t} \in \{0,1\}} u(S_{i,t}, d_{i,t}; \theta) - d_{i,t} \, C(S_{i,t}; \theta) + v_{i,t}^{d_{i,t}} + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t}) \tag{8}
$$

$$
= \max\{ v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 0), \; v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 1) \} \tag{9}
$$

11

$$= \max\{u(S_{i,t}, d_{i,t} = 0; \theta) + v_{i,t}^0 + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 0), \tag{10}$$

$$u(S_{i,t}, d_{i,t} = 1; \theta) - C(S_{i,t}; \theta) + v_{i,t}^1 + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 1)\}. \tag{11}$$

The representation of value function for packages with Python 3 support is more straightforward, since the irreversibility condition implies that no further decisions are being made:

$$V_\theta(S_{i,t}, d_{i,t-1} = 1) \tag{12}$$

$$= v_\theta(S_{i,t}, d_{i,t-1} = 1, d_{i,t} = 1) \tag{13}$$

$$= \mathbf{E}_t\{\sum_{\tau=0}^{\infty} \beta_i^\tau \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big)|S_{i,t}; \theta\} \tag{14}$$

$$= \sum_{\tau=0}^{\infty} \beta_i^\tau \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big) dF_\theta(S_{i,t+1}|S_{i,t}). \tag{15}$$

We assume that $v_{i,t}^{d_{i,t}}$ are independently and identically distributed according to the type I extreme value distribution. Then the expected value function $\mathbf{E}_t V_\theta(S_{i,t+1}|S_{i,t}, d_{i,t})$ can be calculated using the following equation:

$$\mathbf{E}_t V_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 0) \tag{16}$$

$$= \int V_\theta(S_{i,t+1}, d_{i,t} = 0) dF_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 0) \tag{17}$$

$$= \int \log\{\sum_{d_{i,t+1}\in\{0,1\}} \exp(v_\theta(S_{i,t+1}, d_{i,t} = 0, d_{i,t+1}))\} dF_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 0) \tag{18}$$

$$\mathbf{E}_t V_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 1) \tag{19}$$

$$= \int V_\theta(S_{i,t+1}, d_{i,t} = 1) dF_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 1) \tag{20}$$

$$= \sum_{\tau=1}^{\infty} \beta_i^{\tau-1} \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big) dF_\theta(S_{i,t+1}|S_{i,t}, d_{i,t} = 1). \tag{21}$$

Given the parameter θ and the transition dynamics described by F_θ, EV is iterated until convergence, which is then used to calculate choice-specific value functions $v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t})$. The choice-specific value functions allow us to compute the predicted probability of adopting Python 3 using the standard logit formula:

$$P(d_{i,t} = 1|S_{i,t}, d_{i,t-1} = 0; \theta) = \frac{v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 1)}{\sum_{d'\in\{0,1\}} v_\theta(S_{i,t}, d_{i,t-1} = 0, d')} \tag{22}$$

$$P(d_{i,t} = 0|S_{i,t}, d_{i,t-1} = 0; \theta) = 1 - P(d_{i,t} = 0|S_{i,t}, d_{i,t-1} = 0; \theta) \tag{23}$$

$$P(d_{i,t} = 1|S_{i,t}, d_{i,t-1} = 1; \theta) = 1 \tag{24}$$

$$P(d_{i,t} = 0|S_{i,t}, d_{i,t-1} = 1; \theta) = 0. \tag{25}$$

4.2 Payoff Function

As discussed in Section 2, for any of the most commonly-known motivations to contribute to the OSS development, contributors should prefer having more user downloads. Therefore, following the literature of OSS (Fershtman and Gandal (2011) and Fershtman (2016)), we model the payoff of package developers as a function of user downloads. Denote $x_{i,t}$ as the logrithm of total number of times a package i is downloaded by users in period t. We specify the payoff function as a linear function of user downloads:

$$u(S_{i,t}, d_{i,t}; \theta) = \alpha^x x_{i,t}(x_{i,t-1}, d_{i,t}; \theta). \tag{26}$$

Furthermore, we assume that the evolution of the demand follows a first-order Markov process:

$$x_{i,t} = \rho_0 + \rho_1 \cdot x_{i,t-1} + \rho_3 \cdot ds_{i,t} \tag{27}$$
$$+ (\rho_2 \cdot x_{i,t-1} + \rho_4 \cdot ds_{i,t} + \rho_r \cdot r_t) \cdot d_{i,t} + \epsilon_{i,t} \tag{28}$$

where d indicates a package i's adoption status/decision $d_{i,t}$; $ds_{i,t}$ is the number of packages who specify i as their dependency package, i.e. the number of i's downstream packages; r_t is the current Python 3 adoption rate among all packages; $\epsilon_{i,t}^0$ and $\epsilon_{i,t}^1$ are two white noises that are normally and interdependently distributed with mean 0 and variance σ_ϵ^2.[26]

In particular, in order to make our model more general, our model tries to capture the heterogeneities of adoption benefit in two dimensions: the timing of adoption and the characteristics of a package. From equation 28, the additional benefit of package i adopting at time t is:

$$\frac{\partial}{\partial d_{it}} x_{it} = \rho_2 \cdot x_{i,t-1} + \rho_4 \cdot ds_{i,t} + \rho_r \cdot r_t.$$

The first two components capture heterogeneity in adoption benefits due to the popularity and importance of a package. A package with a large existing Python 2 user base is also more likely to have a significant additional potential users on Python 3. The adoption by an important package with many downstream packages might cause a cascade effect for many others, and such a package itself also benefit from the direct downloads from it. The third component captures the timing of adoption. When Python 3 is not widely adopted, the potential Python 3 user base is small, thus a package doesn't gain many downloads from adopting Python 3.

We model user demand with a parsimonious first-order Markov process instead of a structural model of user adoption mostly due to data limitations. We only observe the total number of downloads for each file of a package, which is not equivalent to the user base because a user can download a package multiple times. More importantly, without user identifiers such as IP addresses, there is no way to identify the Python adoption decision for each individual. We assume symmetric information in terms of user dwonloads because package developers have no more downloads statistics than the econometricians. Lastly, the parsimonious first-order Markov process can well capture the variations of downloads in the

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[26]In the estimation of the user downloads function, we assume that package developers can perfectly predict the future values of r_t.

data (see Section 6).

4.3   Adoption Cost

We model the cost function as a function of an agent's decision $d_{i,t}$, lines of code $s_{i,t}$, and the number of incompatible dependencies $\mu_{i,t}$ (adjusted by an "importance" measure of that dependency). The switching cost is thereby defined as below:

$$C_{i,t} = c_0 + \alpha^\mu \, \mu_{i,t} + \alpha^s \, s_{i,t}, \tag{29}$$

and we further assume that $\mu_{i,t}$ is specified as the following:

$$\mu_{i,t} = \sum_{j \in U_i} \mathbf{1}\{d_{j,t} = 0\} \, s_{j,t}, \tag{30}$$

meaning the number of incompatible dependencies weighted by package sizes. We prefer this to the raw number of dependencies because in reality, the cost to deal with an incompatible dependency might be heterogeneous. For example, it may be easier to find a dependency alternative for another small dependency compared to a large one.

The fixed component c_0 of the adoption cost captures all other costs not caputured by $\mu_{i,t}$ and $s_{i,t}$. One important component is the differences between Python 2 and 3, or the difficulty level for a developer to learn Python 3. Since it's a one-time cost, c_0 also includes the present value of future maintenance cost.

Assumption 1. *At time t, a package i observes Python 3 adoption decisions made by its dependencies, namely, $d_{j,t}$ for all $j \in U_{i,t}$.*

This is an assumption on the information set available to a package when making decisions. In particular, the question is whether package i observes the adoption decisions of its dependencies $j \in U_{i,t}$ before making its own adoption decision. If yes (as in Assumption 1), then it's more appropriate to model a sequential move game; if not, then a simultaneous-move game would be more appropriate.

We prefer the sequential-move assumption instead of a simultaneous one due to the following reasons: First, upstream packages tend to be the more popular ones who often pre-announce their plans for future releases, including the Python 3 adoption decisions. Second, a downstream package is likely to pay close attention to decisions made by its dependencies because it directly depends on them in order to work. Thus, it is likely that the Python 3 adoption decisions of upstream packages are readily available to downstream packages as soon as they are made.

Assumption 1 implies upstream packages make decisions first, followed by the downstream packages. The exact order of play in the model is defined based on the network structures, and it will be specified in detail in Section 5.1.

We do not think that a simultaneous-move assumption and a sequential one would produce significantly different results. The only observations that cause different estimates are

cases when a package and its dependencies adopt Python 3 in the same time period, which does not represent a large share in the data.[27]

Assumption 2. *A package i does not explictly consider responses from its downstream packages k where $i \in U_{k,t}$.*

A package i cares about the responses from its downstream packages insofar as it cares about more user downloads of its own package. The mean effect is captured and approximated by the parsimonious first-order Markov process of user downloads, which includes both package and network characteristics. Assumption 2 implies that a package does not explicitly include the response function of its downstream packages in its utility function. Without explicitly modeling the interaction of upstream and downstream packages, assumption 2 significantly reduces the computational burden.

We believe that Assumption 2 is reasonable because upstream packages tend to experience significantly more downloads than their downstream counterparts, in another word, it's likely that indirect downloads through downstream packages account for a small portion of total user downloads.[28] Moreover, an upstream package often has many downstream packages and it's unlikely to track all the downstream packages dependent on it.

4.4 State Variables & Transition Probability

As mentioned in the previous sections, one important component of the adoption cost comes from the dependency network when the dependency packages lack Python 3 support, which is represented by the last component of the state variables $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$. We model a dynamic model of sequential decisions where upstream packages make adoption decisions before downstream packages, and downstream packages observe the decisions made by upstream packages at time t, namely $d_{j,t}$.

Package i cares about the decisions and states of its dependencies $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$ in so far as it cares about its own adoption cost (a function of $\mu_{i,t}$), as well as its future evolution given the current states. The law of motion of $\mu_{i,t}$ can be expressed in the following way:

$$\mathbf{P}(\mu_{i,t+1} = \mu' | \mu_{i,t} = \mu, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}; \theta)$$
$$= \mathbf{P}(\mu' | \mu, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}; \theta), \tag{31}$$

where $\mu \geq \mu'$, meaing that the adoption cost in future periods might be lower. The component $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$ is important to predict the future adoption probabilities of dependency j. Denote the probability of dependency j adopting and not adopting Python 3 as $\widehat{p}^1_{j,t+1} = \mathbf{P}(d_{j,t+1} = 1 | d_{j,t} = 0, S_{j,t}; \theta)$ and $\widehat{p}^0_{j,t+1} = \mathbf{P}(d_{j,t+1} = 0 | d_{j,t} = 0, S_{j,t}; \theta)$, respectively. Further, we define the set of dependencies without Python 3 support as $\Omega_{i,t} \equiv \{j \in U_{i,t}, d_{j,t} = 0\}$. Then we can simplify equation 31 as:

$$\mathbf{P}(\mu' | \mu, \{\widehat{p}_{j,t+1}\}_{j \in \Omega_{i,t}}; \theta). \tag{32}$$

---

[27]If package i observes $d_{j,t} = 1$, then the perceived adoption cost is much smaller than the case without observing $d_{j,t}$. In this case, the cost parameter with a simultaneous-move model is smaller compared to a sequential-move version.

[28]Unfortunately, neither the econometrician nor the packages have a clear knowledge regarding the portion of downloads coming from direct versus indirect channels.

Note that μ is defined as the number of incompatible dependencies weighted by the package size. It is a deterministic function of the set of incompatible dependencies. Thus the transition probability of μ is equivalent to that of the set of incompatible dependencies. Define $\mathcal{O}_{i,t}$ as the power set of $\Omega_{i,t}$ that contains all possible subsets of $\Omega_{i,t}$, then the equations above can be further simplied as:

$$\mathbf{P}(o' \mid \Omega_{i,t}, \{\widehat{p}_{j,t+1}\}_{j\in\Omega_{i,t}}; \theta) \tag{33}$$

$$= \prod_{j\in o'} \widehat{p}^0_{j,t+1} \prod_{j\in\Omega_{i,t}\backslash o'} \widehat{p}^1_{j,t+1}, \tag{34}$$

where $o' \in \mathcal{O}_{i,t}$, $\mu = \sum_{j\in\Omega_{i,t}} s_{j,t}$, and $\mu' = \sum_{j\in o'} s_{j,t}$

The mathmatical notation above can be more easily understood with a simple example. Suppose that at time t, package i has three dependencies $U_{i,t} = \{A, B, C\}$, and $d_{A,t} = 0$, $d_{B,t} = 0$, $d_{C,t} = 1$, leaving the set of dependency without Python 3 support as $\Omega_{i,t} = \{A, B\}$. Suppose package i's belief that each of the dependencies will adopt Python 3 at time $t + 1$ with the following probability: $\widehat{p}^1_{A,t+1} = a$, $\widehat{p}^0_{A,t+1} = 1 - a$, $\widehat{p}^1_{B,t+1} = b$, $\widehat{p}^0_{B,t+1} = 1 - b$. The powerset of $\Omega_{i,t}$ is $\mathcal{O}_{i,t} = \{\varnothing, \{A\}, \{B\}, \{A, B\}\}$. Following equation 34, the transition from $\mu = s_A + s_B$ to $\mu' = s_A$ can be calculated as:

$$\mathbf{P}(\mu' = s_A \mid \mu = s_B, \{\widehat{p}_{j,t+1}\}_{j\in\Omega_{i,t}}; \theta) \tag{35}$$

$$= \mathbf{P}(o' = \{A\} \mid \Omega_{i,t} = \{A, B\}, \{\widehat{p}_{j,t+1}\}_{j\in\Omega_{i,t}}; \theta) \tag{36}$$

$$= \prod_{j\in o'} \widehat{p}^0_{j,t+1} \prod_{j\in\Omega_{i,t}\backslash o'} \widehat{p}^1_{j,t+1} \tag{37}$$

$$= \widehat{p}^0_{A,t+1} \cdot \widehat{p}^1_{B,t+1} \tag{38}$$

$$= (1 - a)\, b. \tag{39}$$

4.5   Transition Matrix

The calculation of EV in equation 18 depends crucially on the specification of the transition matrix, or $\mathbf{P}_{S'|S}$.

In our model, the utility function is mainly governed by two variables, namely, $x_{i,t}$, the measure of downloads or popularity, and $\mu_{i,t}$, the measure of adoption cost due to incompatible dependencies. The construction of the transition matrix depends on the joint law of motion of $x_{i,t}$ and $\mu_{i,t}$.

The law of motion of $x_{i,t}$ is relatively simple. We assume that it follows a first-order Markov process specified in equation 28, with the parameter values estimated outside the value function iteration. On the other hand, the law of motion of $\mu_{i,t}$ is much more difficult.

Recall that $\mu_{i,t} \equiv \sum_{j\in U_{i,t}} \mathbb{1}(d_{j,t} = 0)\, s_{j,t} \equiv \sum_{j\in\Omega_{i,t}} s_{j,t}$, that is, the number of dependencies of package i without Python 3 support at time t weighted by the package size.

One of the most important tradeoffs for package i to adopt Python 3 today at t vs. future periods $t + \tau$ is the decreasing adoption cost due to the decreasing number of dependencies without Python 3 support over time. Therefore, the solution to the dynamic adoption model depends on the calculation of future adoption probabilities for each of the dependencies.

The calculation is a formidable task due to the nature of the nested dependency network. This computational difficulty can be illustrated by forecasting the Python 3 adoption probability for each of package i's dependency $j \in U_{i,t}$ at time $t+1$:

$$\widehat{p}_{j,t+1}^1 = \int_{S_{j,t+1}} \mathbf{P}(d_{j,t+1} = 1|S_{j,t+1}, d_{j,t} = 0, z_j; \theta) d\mathbf{P}(S_{j,t+1}|S_{j,t}, d_{j,t} = 0, z_j; \theta). \quad (40)$$

The integral can then be computed through a simulation of future states $S_{j,t+1}$. Let $S_{j,t+1}^m$ be the mth simulation, then the value of $\widehat{p_{j,t+1}^1}$ can be obtained by:

$$\widehat{p}_{j,t+1}^1 = \frac{1}{M} \sum_{m=1}^{M} \mathbf{P}(d_{j,t+1} = 1|S_{j,t+1}^m, d_{j,t} = 0, z_j; \theta). \quad (41)$$

This simulation method can be very computationally intensive. Note that the nested states are expressed as $(x_{i,t-1}, d_{i,t-1}, \nu_{i,t}, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}})$. The simulation of the states of package j requires the simulation of the states of j's dependency $k \in U_{j,t+1}$, as well as the states of k's dependencies, and so on. Any slight changes in any of the linked dependencies, or the dependencies of each dependency, can affect $p_{j,t}$. In this way, the full solution approach by Rust (1987) is no longer feasible due to the curse of dimensionality problem. In fact, with the 3,102 packages and 13,056 observations, it is simpler to build the transition matrix dynamically for each package i at each time period t. In later Section 5, we list the detailed steps outlining how to compute $p_{j,t}$ for $j \in \Omega_{i,t}$ given the input-output network.

A transition matrix used for the dynamic programming problem includes the transition probability, not only from the current state to the next, but also from each of the possible states to all other states. Given the state $S_{i,t}$, package i calculates $\widehat{p}_{j,t+\tau}^1$ for each of $j \in \Omega_{i,t}$ and $\tau \in \mathbb{N}$.

Given the transition probability specified in equation 34, the full transition matrix needed to calculate $EV(S, d = 0; \theta)$ can be specified as the following:

$$P(o' \in O_{i,t}|o \in O_{i,t}) = \begin{cases} 0 & \text{if } o \not\subseteq o' \\ \prod_{j \in o'} \widehat{p}_{j,t}^0 \prod_{j \in o \setminus o'} \widehat{p}_{j,t}^1 & \text{if } o \subseteq o' \end{cases}. \quad (42)$$

The calculation of the transition matrix, as specified in equation 42, can be illustrated using the same example in Section 4.4. Recall that the set of dependencies without Python 3 support is $\Omega_{i,t} = \{A, B\}$. The adoption probability of A and B at time t can be calculated by package i. Assume that $\widehat{p}_{A,t+1}^1 = a$ and $\widehat{p}_{B,t+1}^1 = b$. The powerset of $\Omega_{i,t}$ is $O_{i,t} = \{\varnothing, \{A\}, \{B\}, \{A, B\}\}$, and $O_{i,t}^0 = \{\varnothing\}$. Therefore, the transition matrix of μ can be

calculated using equation 42:

$$
TM(\mu_{i,t}) = \begin{array}{c} \\ \{A,B\} \\ \{A\} \\ \{B\} \\ \varnothing \end{array} \begin{array}{cccc} \{A,B\} & \{A\} & \{B\} & \varnothing \\ \left[\begin{array}{cccc} (1-a)(1-b) & a(1-b) & (1-a)b & ab \\ 0 & 1-a & 0 & a \\ 0 & 0 & 1-b & b \\ 0 & 0 & 0 & 1 \end{array}\right]. \end{array}
$$

The corresponding value of μ for each row (or column) is $s_A + s_B, s_A, s_B, 0$, respectively. By construction, the transition matrix considers both the number and the identities of dependencies that are without Python 3 support. For example, the situation with dependency A being the only one without Python 3 support differs from the situation when B is the only one. Dependency packages A and B differ not only in their sizes that result in different values of $\mu_{i,t}$, but also in other aspects (such as downloads) that affect their own future adoption probabilities which matter for the optional value of waiting for package i. The transition matrix calculated using equation 42 considers of all such cases.

4.6   Discount Factor

To capture the heterogeneity in valuation of future utility, we specify the discount factor β_i as a form of Gumbel function $\mathcal{B}(z_i' \lambda)$:

$$
\beta_i \equiv \mathcal{B}(z_i' \lambda) = 1 - e^{-e^{z_i' \lambda}} \tag{43}
$$

$$
\text{where } z_i' \lambda = \lambda_0 + \lambda_1 \, Releases_i + \lambda_2 \, Files_i \tag{44}
$$

$$
+ \lambda_3 \, Description_i + \lambda_4 \, Classifiers_i.
$$

The Gumbel specification has an important advantage in numerical estimation because for any value of the argument $z_i' \lambda$, $\mathcal{B}(z_i' \lambda)$ is by definition bounded within 0 and 1, and no further constraints are needed. We further specify $z_i' \lambda$ as a linear function of several variables that can potentially affect how package developers value future downloads but not its Python 3 adoption decisions: $Releases_i$: average number of releases per year; $Files_i$: average number of files contained in each release;[29] $Description_i$: average number of characters used in the description section; $Classifiers_i$: average number of classifiers (similar to tags or labels) associated with each package.[30]

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[29]For each release of a package, there can be multiple files for different operating systems (Windows, macOS, Linux, etc) and for different Python versions.

[30]Some examples of "Classifiers" include: Environment - Web Environment, Intended Audience - Science/Research, License - OSI Approved - MIT License, Topic - Internet - WWW/HTTP.

5 Identification & Estimation

The parameters of interest in our model are the following:

$$\theta = \Big\{\underbrace{\rho_0, \rho_1, \rho_2, \rho_3, \rho_4, \rho_r}_{\theta_D};\ \underbrace{c_0, \alpha^\mu, \alpha^s, \lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4}_{\theta_S}\Big\}.$$

The parameters can be grouped into two subsets θ_D and θ_S. θ_D includes parameters of the demand function, the process of user downloads modeled as a first-order Markov process; θ_S includes parameters of the supply side, which is the structral model of technology adoption by package developers.

5.1 Identification

The set of demand-side parameters $\theta_D = \{\rho_0, \rho_1, \rho_2, \rho_3, \rho_4, \rho_r\}$ can be identified from the variation of x_t over time. Following the existing literature of dynamic discrete choice models (Keane (1994), Keane and Wolpin (1997)), we estimate the Markov process separately from the structural model of technology adoption for reason mentioned in 4.2.

One major concern is that the estimates of the AR1 process may suffer from an endogeneity problem. The AR1 process is estimated using the evolution of user downloads as a result of the actual adoption decision. The packages that have adopted Python 3 may experience a positive persistent demand shock that is unobservable to the econometrician. In other words, due to the endogeneity issue, the benefit of Python 3 adoption inferred by the AR1 estimates can be over-exaggerated. To correct the endogeneity problem, we instrument the adoption decision $d_{i,t}$ using package characteristics such as the number of downloads and package size.[31]

Then the estimates of the AR1 process of x are used as inputs for the structural model of technology adoption. The fixed cost c_0, the cost due to the network α^μ, and the cost due to package size α^s are identified through the variations of x, μ, s and the adoption decisions d.

In most settings of dynamic discrete choice models, the discount factor is not separately identified from other parameters (Magnac and Thesmar (2002)). In our setting, all utilities are measured in terms of user downloads. As a result, α^x and β_i play a similar role in the model. The identification of the discount factor requires certain variations that shift future but not current utility (Abbring and Daljord). In theory, such variations can be found in our data: Imagine a case where two packages A and B who are identical in every way except their dependencies who have the same sizes. In this case, A and B also face identical adoption cost with the same μ. However, due to differences in other characteristics of their dependencies (such as downloads), the dependencies can have different future adoption probabilities, which in turn affects the optional value of waiting for A and B. In practice, however, there are

---

[31] As robustness check, we also conducted a two-step estimation approach using a synthetic instrumental variable. Given an initial set of AR1 estimates, we first estimate the model of technology adoption. Then in the second step, we use the predicted adoption probability as an instrumental for the endogeneous variable $d_{i,t}$ and re-estimate the AR1 process. Then the new estimates are fed back to step 1 to re-estimate the model of technology adoption. Step 1 and 2 are repeated until all of the estimates converge to a fixed point.

very few cases, and the identification power from this source is rather weak.[32]

By fixing the value of α^x, we can identify the discount factor through the differences in package-specific characteristics, which affect package developers' intertemporal trade-off between short term adoption cost and long term benefit, which is exogenously given from the demand side. For example, two packages face identical adoption costs, but have slightly differences in user downloads. Assume the initial differences in downloads also lead to persistent long-term differences. If such small differences lead to large disprepancies in their adoption probability, it means that packages are more patient, and vice versa.

In this paper, we fix the value of α^x to 1. Note that the demand side of user downloads is estimated separately. Fixing α^x means fixing current period's utility per unit of download. With that, we allow β to vary with certain package characteristics that are unlikely to affect the adoption decisions. The discount-factor-related parameters λs are identified through the variations of such variables and the observed adoption decisions. For example, a package with many "classifiers" is likely to put more weight on the additional downloads as a result of Python 3 adoption.

5.2   Estimation Method

Our model of technology adoption is estimated using the Maximum Likelihood Estimation (MLE) method. The likelihood function is defined as:

$$l(\theta) = \prod_{i=1}^{N}\prod_{t=1}^{T_i} \widehat{p}_{i,t}^{0}{}^{\mathbf{1}\{d_{i,t}=0\}} \widehat{p}_{i,t}^{1}{}^{\mathbf{1}\{d_{i,t}=1\}},$$

where $\widehat{p}_{i,t}^{1} \equiv \widehat{p}^1(S_{i,t}; \theta)$ as defined in equation 22.

The adoption decision of a package i depends crucially on the adoption status of its dependencies, which is summarized as $\mu_{i,t}$ in the utility function. Further, Assumption 1 states that $\mu_{i,t}$ is known to package i before making decisions at t. It allows us to model and calculate Python 3 adoption probability for packages sequentially.[33] To do this, we first group all packages into L sets based on their acyclical dependency relationship: $\mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3, \cdots, \mathcal{L}_L$ where $\mathcal{L}_l$ is defined as:

$$\mathcal{L}_l = \{i| \max_{j} n_{ji} = l - 1 \quad \forall j \in N\},$$

where N is the set of all packages and n_{ji} is the minimal length of all directed acyclical graph from package j to i. Figure 5 depicts layered network representation using a small sample of Python packages.

In every time period t, packages in layer 1 decide to adopt Python 3, followed by those in

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[32]That is to say, the nonlinear optimizer still returns reasonable estimates but the objective function is nearly flat near the solution.

[33]Assumption 1 simplifies our model estimation but only slightly. Compared to a simultaneous-move version, the set of dependencies without Python 3 support at time t under the current assumption is weakly smaller, which can alleviate the computational burden in cases where both the upstream and downstream packages adopt Python 3 in the same time period, and such cases comprises a small percentages of cases in the data.
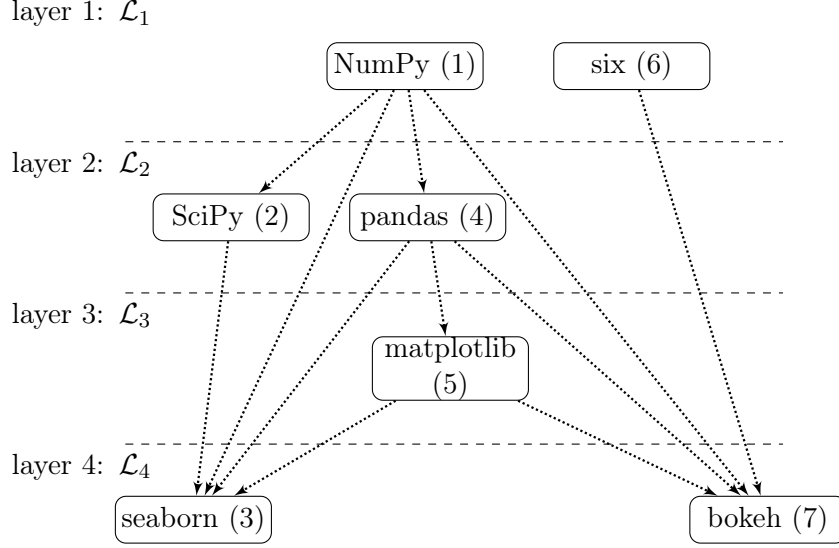
layer 1: $\mathcal{L}_1$

Figure 5: Example of the Layered Network Representation

layer 2, then those in layer 3,$\cdots$, etc. The probability of adopting Python 3 for each of the upstream packages is then used as given for the decision making process of the downstream package, in order to calculate the transition probability of $\mu_{i,t}$.

Regarding the timing, we summarize all the variables to six-month periods to fit our dynamic discrete-choice model. For example, 2013/01/01 to 2013/06/30 is one period, and 2013/07/01 to 2013/12/31 is another.

Our algorithm begins by setting initial values for θ_D, which comes from OLS estimation of the AR1 process of user downloads, specified in equation 28. Estimation then involves iteration on the four steps, where the mth iteration follows:

Step 1: Estimate Demand Parameters θ_D Using IV

- Estimate the first-order Markov process of demand function using $x_{i,t}, \mu_{i,t}, s_{i,t}$ as IV with the standard IV estimation method.

Step 2: Estimation of the Model of Technology Adoption

- Given estimates of demand function θ_D and an initial guess of θ_S:

    - for $i \in \mathcal{L}_1$, build transition matrix for each i, t and calculate $\widehat{p}^1(S_{i,t}; \theta)$
    - for $i \in \mathcal{L}_2$, given $\widehat{p}^1(S_{j,t}; \theta) \ \forall j \in \mathcal{L}_1$, build transition matrix for each i, t and calculate $\widehat{p}^1(S_{i,t}; \theta)$
    - for $i \in \mathcal{L}_3$, given $\widehat{p}^1(S_{j,t}; \theta) \ \forall j \in \mathcal{L}_{1,2}$, build transition matrix for each i, t and calculate $\widehat{p}^1(S_{i,t}; \theta)$

    $\vdots$

    - for $i \in \mathcal{L}_l$, given $\widehat{p}^1(S_{j,t}; \theta) \ \forall j \in \mathcal{L}_{1,2,\cdots,l-1}$, build transition matrix for each i, t and calculate $\widehat{p}^1(S_{i,t}; \theta)$

21

$\vdots$

  - for $i \in \mathcal{L}_L$, given $\widehat{p}^1(S_{j,t}; \theta) \ \forall j \in \mathcal{L}_{1,2,\cdots,L-1}$, build transition matrix for each i, t and calculate $\widehat{p}^1(S_{i,t}; \theta)$

- Calculate likelihood fuction $l(\theta)$

- Update θ such that $\theta_S^* = \operatorname*{argmax}\limits_{\theta_S} l(\theta_S, \theta_D)$.

6　Results

Table 4: Estimation of Download Process (First-Order Markov)

	(1) OLS	(2) IV
$x_{i,t-1}$	0.779***	0.788***
	(0.00)	(0.00)
$ds_{i,t}$	0.167***	0.167***
	(0.00)	(0.01)
$d_{i,t} \times x_{i,t-1}$	-0.002	-0.014***
	(0.00)	(0.00)
$d_{i,t} \times ds_{i,t}$	0.080***	0.086***
	(0.01)	(0.01)
$d_{i,t} \times r_t$	0.216***	0.314***
	(0.03)	(0.03)
Constant	2.001***	1.958***
	(0.02)	(0.02)
N	46266	46266
R^2	0.831	0.831

Table 4 summarizes the parameter estimates of the download process, modeled as a first-order Markov process specified in equation 28. Column 1 shows results from OLS regression and column 2 corrects the endogeneity of $d_{i,t}$ as explained in Section 5.

Both OLS and IV estimation results indicate heterogeneous effects on downloads after adopting Python 3. When Python 3 is not yet widely adopted (low r_t), a package with few downstream packages (low $ds_{i,t}$) might find Python 3 adoption hurting the number of downloads. It's likely due to the time constraint faced by package developers: more time spent to adopt Python 3 means less time to make improvements to the existing Python 2 version of the package. However, the incentive for packages with more downstream packages can be much larger. Once such a package adopts Python 3, it clears an important roadblock for its downstream packages and allows them to adopt Python 3 with less cost. The upstream package itself also benefits because it gets both direct downloads from end users and indirect downloads through the installation of its downstream packages. The benefits of such cascade effect is captured through $ds_{i,t}$ in this downloads process.

Table 5: Parameter Estimates of Adoption Model (θ_S)

Cost	c_0	-1.741***
Parameters		(-19.741)
	α^μ	-0.24***
		(-13.78)
	α^s	-0.103***
		(-5.153)
Discount Factor	λ_0	-0.736***
Parameters		(-3.055)
	λ_1	0.18***
		(6.021)
	λ_2	-0.412***
		(-3.565)
	λ_3	0.03
		(0.638)
	λ_4	0.258***
		(4.931)
Log Likelihood		-6749
Number of Packages		3397
Number of Observations		18916

Table 5 summarizes the estimation results of the structral model of technology adoption. It lists the parameter estimates of the cost function and the discount factor in separate parts.

The cost function of adopting Python 3 has three components: 1. fixed adoption cost c_0; 2. cost to deal with dependencies without Python 3 support $\alpha^\mu \mu_{i,t}$; 3. cost to update one's own code $\alpha^s s_{i,t}$. Both $\mu_{i,t}$ and $s_{i,t}$ are measured in the unit of logrithm of file sizes, and packages differ significantly in their sizes. To contrast the magnitude of the cost components, we plot the distribution of costs due to one incompatible dependency and updating one's own package in Figure 6. The average logrithm of package size for a dependency is 5.05, and the average cost of dealing with one incompatible dependency is $\alpha^\mu \times 5.05 = 1.21$. In comparison, the average size for a package is 4.52, and the average cost of updating one's code is $\alpha^s \times 4.52 = 0.46$, which is roughly one-third the cost to deal with one incompatible dependency. The relative high cost of dealing with one incompatible dependency is not too surprising. Package developers are more familiar to their own code and less so with the functionalities provided by a dependency package; thus, manually updating part of the code from a dependency for one's own use can be cahllenging. At the same time, it's not always easy to find a good alterantive package that provides exactly the same functionality as the existing dependency.[34]

The rich specification of the discount factor in equation 44 allows us to examine the heterogeneity in the way different packages value future changes in cost and benefits.

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[34]In theory, the cost to deal with an incompatible dependency depends how the availability of alternative packages. Unfortunately we are unable to account for this factor in the cost function due to a lack of systematic method to identify competing packages.
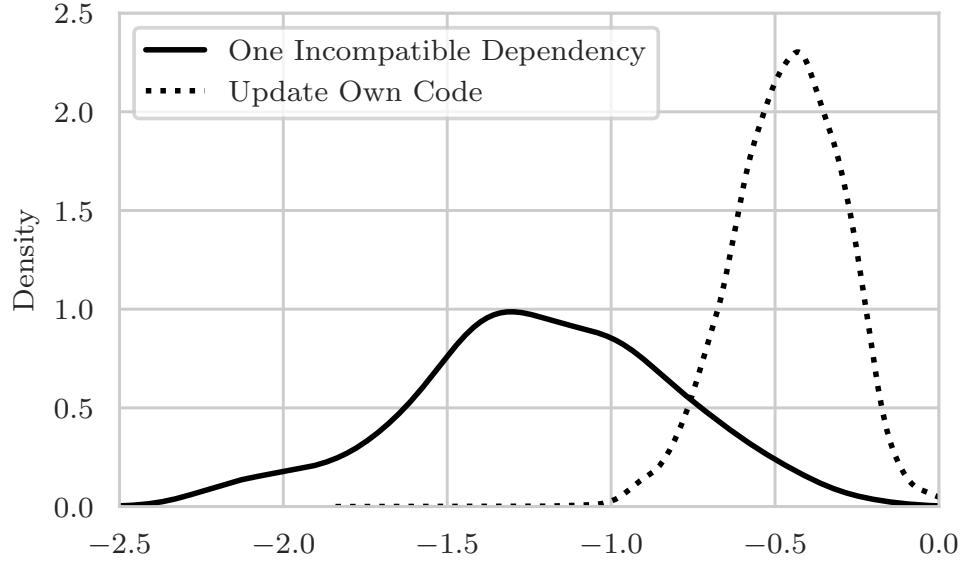
Figure 6: Variable cost due to one incompatible dependency versus one's own code (convert α^μ, α^s to the same scale)
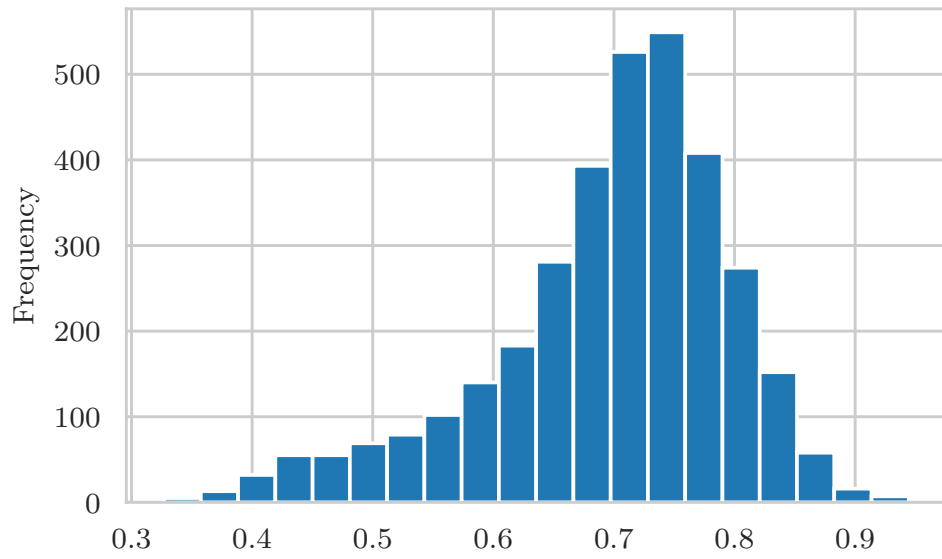

Figure 7: Distribution of Discount Factor $\hat{\beta}_i$

The mean value of β_i for the 3,397 packages used in our analysis is 0.697 (for six months), which is equivalent to an annual discount factor of 0.486. This estimate is much lower compared to the discount factors estimated for other industries (e.g., 0.988 in De Groote and Verboven (2019)). It is not too surprising because OSS differs importantly from other industries due to a lack of explicit pecuniary incentives. To examine the heterogeneity in β_i in detail, we plot the distribution of $\hat{\beta}_i$ in Figure 7. It displays a large dispersion ranging from 0.326 to 0.944 with mode of 0.73.

6.1 Model Fit

One advantage of the structural model is the ability to run simulations. Through simulation, we can examine the goodness of fit of our model by comparing the actual versus simulated adoption rates over time. It can also be considered as cross validating our model by comparing auxiliary information from the data and the model.
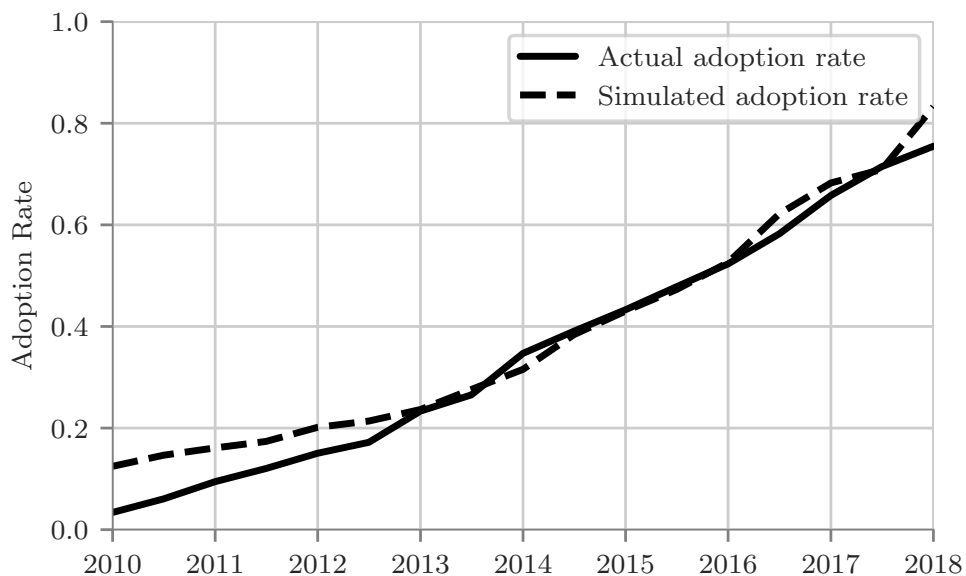

Figure 8: Actual vs. Simulated Adoption Rates

We run simulations of adoption decisions. Based on the states of each time period, we simulate the Python 3 adoption decisions for packages that are still active in that period. We run the same simulation for 100 times and plot the average simulated adoption rate against the actual rate in Figure 8. The simulated adoption curve follows closely to the actual one except in the first few periods where the simulation over-predicts the adoption by 5% to 10%.

7 Counterfactuals

Katz and Shapiro (1985) predict that the success of a new technology and the speed of technology adoption highly depends on "sponsorship". A sponsor is an entity that is

willing to make an investment to promote a new technology. There exists such a sponsor in the Python programming language—namely, Python Software Foundation (PSF). It is a nonprofit organization that oversees various issues in the Python community, including the transition from Python 2 to 3. Given limited amount of resources, it is critical to understand how the to efficiently allocate its resources to avoid excess adoption inertia and promote a faster pace towards Python 3.[35]

In this section, we examine the effectiveness of two counterfactual policies to promote a faster Python 3 adoption: lower fixed adoption cost and community-level targeted subsidy. The first policy helps us to understand how much Python 3 adoption is affected by the fixed component of the adoption cost; the second one attempts to seek an "optimal" policy of cost subsidies to various sub-communities within Python.

7.1 Lower Fixed Adoption Cost

For this counterfactual exercise, we study how the Python 3 adoption decisions would respond to a lower fixed adoption cost c_0. As explained in Section 4.3, the fixed adoption cost comes from multiple sources: e.g. differences in the language syntax and usage and maitenance cost of future releases of a package. For PSF, there are multiple ways to achieve a lower c_0 for the entire Python community: e.g. better automatic converion tool from Python 2 to 3 and higher level of compatibility through scheduled deprecation.[36] We abstract away from the specific ways that PSF can lower c_0 and focus instead on the effect of a lower c_0 on the dynamics of Python 3 adoption over time.

Figure 9 contrasts the simulated adoption rates with and without the policy. Based on the state variables of 2010, we simulate adoption curves under two levels of fixed costs and draw the average adoption curve in Figure 9. We find that a one-third reduction in the fixed adoption cost leads to roughly 12% increase in adoption rate by the end of 2018. The gap is small at the beginning, and it grows and stabilizes by 2018 as it gets closer to 100%. In particular, to reach an adoption rate of 40%, the cost reduction can help accelerate by two years from 2015 to 2013.

7.2 community-level targeted Subsidy

The first counterfactual exercise studies the effects of a lower adoption cost for the whole Python community. In reality, lowering adoption cost for the whole Python programming language might be difficult due to a high development cost. An alternative way to promote Python 3 is through cost subsidies. Python has been used by many domains and each form its own community through specialized packages. Given limited resources, PSF can focus on providing subsidies to certain communities that are most reluctant to adopt Python 3 without such subsidy. In this subsection, we will investigate how subsidies to one community can affect its adoption rate over time, as well as its propagation effect on other connected

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[35]Excess inertia refers to slow adoption despite user benefits of new technology (Farrell and Saloner (1985)).

[36]We do not study the optimal compatibility decision made by PSF in this paper. The official reason for the incompatiblity between Python 2 and 3 is a high development cost. In this paper, we focus on measuring the benefits of lower adoption cost.
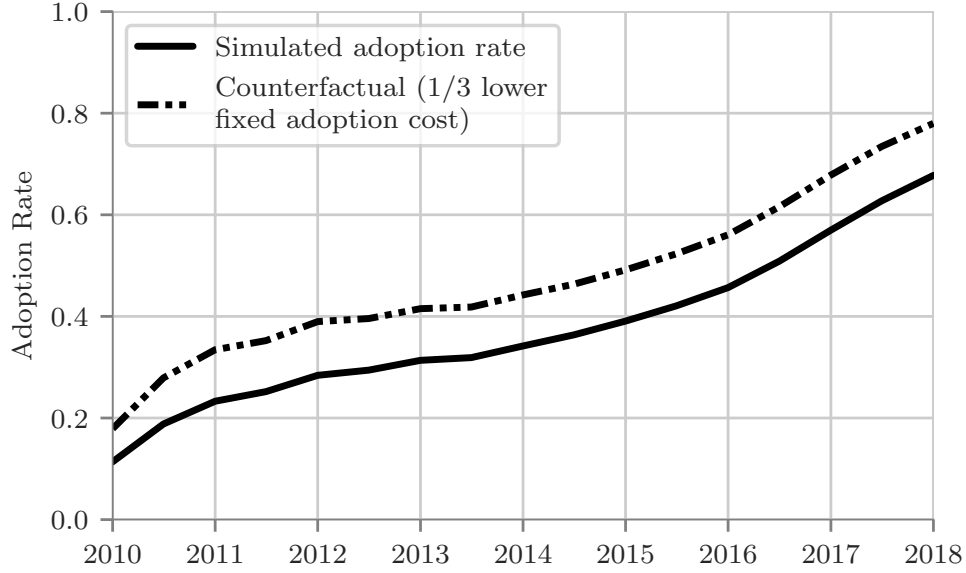
Figure 9: Simulated Adoption Rate With Lower Adoption Cost

communities.[37]

7.2.1 Communities in Python

Python is a general-purpose programming language, meaning that it is not designed for a specific community of users; rather, it is designed in a flexible way so that users from any domains can customize it for their own use (e.g., data analysis and web development). The needs of communities are met by third-party packages, most of which are designed to achieve certain tasks in their specific fields. Those packages that serve users within a given community tend to be more closely linked through dependencies.

The Louvain community detection algorithm (Blondel et al. (2008)) helps us to re-adjust the adjacency matrix which clusters packages into six major communities. Figure 10 plots the updated adjacency matrix. Each dot represent a dependency between two packages; each square represents a community: a larger one means more packages and a darker one shows denser links among packages within that community. Packages are more densely linked within the community and less so across communities. A handful of packages (those with long vertical lines) are used as dependencies by many packages across different communities.

Tables 6 describe the functionalities and characteristics of packages for each community. In the Appendix, Figure 11 plots the network structure for each of the communities.

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[37]Another example is similar subsidy can be found in artificial intelligence (AI). AI adoption can be beneficial in many fields, but how should the government allocate its promotion resources? See https://esrc.ukri.org/funding/funding-opportunities/canada-uk-artificial-intelligence-initiative-building-competitive-and-resilient-economies-and-societies-through-responsible-ai/ for a recent example.
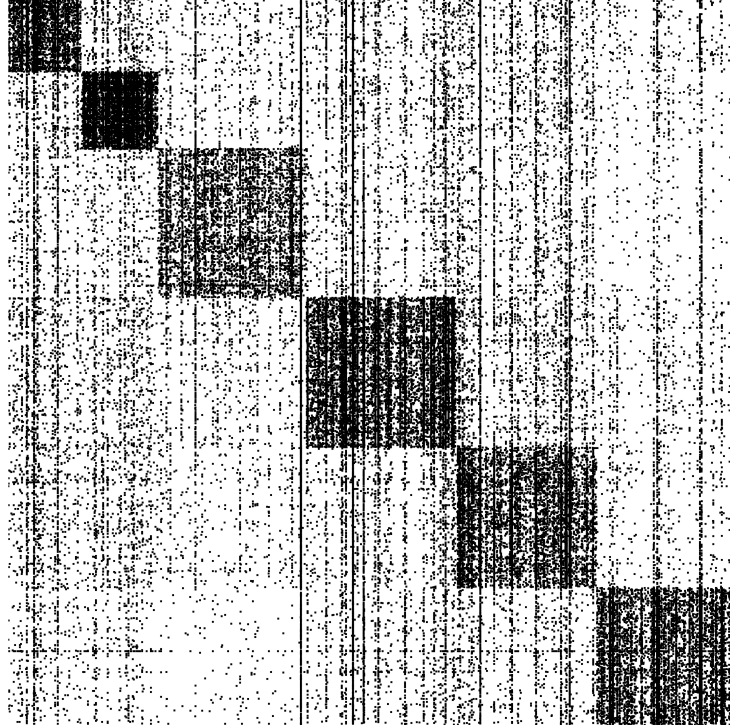
Figure 10: Python Community Through Dependency Network

7.2.2 Policy Evaluation

We examine the effectiveness of community-level targeted subsidy on the adoption rates through both direct effects within that community and indirect effects on other communities, because communities are all linked in different ways. For each community, we adopt a cost subsidy policy which lowers the fixed adoption cost by one-third starting from 2010. We run the simulation of such policies for each of the seven communities for 100 times each. Then we compare the differences between community-level adoption rates with and without the subsidy.

The effectiveness of community-level adoption rate to subsidies is reported in Table 7. Each row represents a targeted community that receives a subsidy equaling to one-third of the fixed adoption cost c_0. Each column shows the changes of community-level adoption rates. For example, the subsidy received by community 1 has caused 7.31% higher adoption in community 1 and 0.38% higher in community 2 after three years. The digonal elements represents the within-community effects and the off-diagonal elements are across-community effects of the subsidy.

Based on the 100 simulations, we also report the significance rates. A significance of 5% means that more than 95 out of the 100 simulation results show the policy accelerates adoption. The results show that the subsidy on a targeted community accelerates adoption in that community. However, the effects on other non-subsidized communities can be positive or negative. On the one hand, more packages in the targeted community adopting Python 3 can result in more adoption of their downstream packages in other communities due to fewer

28

Table 6: Package Characteristics by Community

ID	Description	Num of Packages	Avg Downloads	Avg Size (in KB)	Avg Num of Dependencies	Avg Num of Downstream Pkg
1	database	374	35325	301.851	2.891	2.431
2	cryptography	395	64846	362.081	3.621	2.289
3	web development	684	28189	224.363	2.573	2.215
4	web navigation	405	55461	203.544	2.721	1.982
5	software development	464	32870	368.818	3.194	1.549
6	data analysis	370	16782	777.119	3.091	2.420

Table 7: Effectiveness of Community-Level Subsidy (Year 3)

	1	2	3	4	5	6
1	**7.31%***	0.38%	0.19%	-0.12%	0.27%	-0.98%
2	0.42%	**9.23%***	-0.17%	-0.49%	-0.05%	0.14%
3	-0.54%	0.24%	**8.32%***	-0.21%	0.17%	-0.16%
4	**-0.87%†**	-0.50%	-0.12%	**8.10%***	0.10%	-0.08%
5	-0.77%	-0.59%	0.17%	-0.46%	**9.06%***	0.29%
6	-0.36%	0.55%	0.44%	-0.23%	0.09%	**10.03%***

Notes: siginificance level: * 5% † 10%
Each row represents the targeted community that receive a subsidy equaling to one-third of the fixed adoption cost c_0. The column shows the changes of community-level adoption rates.
This table reports results three years after the cost subsidy.

incompatible dependencies. On the other hand, the subsidy policy increases the adoption probability of packages in the targeted community, thus downstream packages in other communities have more incentive to wait because it is more likely to have a lower adoption cost in the near future. Most of the significant results in across-community effects are actually negative, indicating the latter effect dominates the former in the first three years.

One natural subsequent question is what's the "optimal" policy? Suppose PSF wants to maximize the overall Python 3 adoption but it has only limited resources to provide subsidy, which community should receive it?

The solution to this question needs to account for both the direct effect of subsidy within that community and indirect effect to other communities. Moreover, the temporal dimension also matters. Table 8 summarizes the effectivess of community-level subsidy to the targeted community and overall Python community over time. Each column represent the targetd community m; ΔAR_m represents the difference between the adoption rate in that year with and without the subsidy, and $\Delta OverallAR$ is the difference of overall adoption rates with and without a community-targeted subsidy. For example, subsidy to community 1 increases the community-level adoption by 7.12% and overall rate by 0.70% after one year.

Certain communities have strong reactions to the subsidy but adoption in other communities might stall due to the negative indirect effects. Targeting community 6 can raise its adoption rate by 9.35% but it has a minimal impact of 0.44% for the overal adoption; whereas subsidy to community 3 can achieve a much larger impact of 1.03% depsite a smaller

Table 8: Effectiveness of Community-Level Subsidy

Target Type	1	2	3	4	5	6
Year 1						
ΔAR_m	7.12%	7.98%	6.66%	7.21%	7.16%	9.35%
$\Delta Overall AR$	0.70%	0.46%	1.03%	0.77%	0.83%	0.44%
Year 2						
ΔAR_m	6.88%	9.21%	6.82%	8.73%	8.41%	10.79%
$\Delta Overall AR$	0.71%	0.58%	1.54%	0.81%	1.07%	0.77%
Year 3						
ΔAR_m	7.31%	9.23%	8.32%	8.10%	9.06%	10.03%
$\Delta Overall AR$	0.84%	0.73%	1.86%	0.82%	1.13%	0.63%
Year 5						
ΔAR_m	9.27%	9.88%	10.18%	9.20%	9.22%	8.59%
$\Delta Overall AR$	1.06%	1.11%	2.18%	1.13%	1.23%	0.84%
Year 8						
ΔAR_m	11.22%	11.35%	9.66%	9.48%	9.95%	10.58%
$\Delta Overall AR$	1.29%	1.37%	2.00%	1.28%	1.31%	1.59%

within-community effect of 6.66%. Similar results hold for the long run as well.

The "optimal" policy also depends on the temporal dimension. For example, to maximize the overall adoption, community 5 seems to be a better target for cost subsidy than 6 in the short run (0.83% vs. 0.44% in the first year), but the result is reversed in the long run (1.31% vs. 1.59% in the eighth year).

8 Conclusion

Technological changes have been fundamental to the economic growth; however, many new technologies fail to attract quick and widespread adoption. In many cases, fast adoption of new technologies can be socially beneficial: slow adoption often leads to a long period with incompatible products, while a more rapid adoption enables consumers to better enjoy the convenience brought by the latest technology.

Our research explores how technology adoption can be affected by network structures in a disaggregated input-output network. We build a structural model of technology adoption to capture the dynamic compatibility decisions of packages who are inter-linked through a rich input-output network. Our dynamic model allows each agent to anticipate the future actions of others.

The estimation results show the importance of dynamics in our model setting. Compared with a static one, the dynamic model better captures the decision-making process generated by the interactions in the network: we find strong evidence that the adoption decisions of downstream players are significantly affected by their upstream counterparts. It not only gives a better fit, but also implies the interactive elements that can only be captured by a

structural dynamic model.

Through counterfactual analysis, we investigate the optimal policy to accelerate adoption. Simulation results show that when providing subsidies to a certain community of the population, the optimal policy highly depends on the network of both the targeted community and the interaction with other communities. Moreover, the time horizon aspect is also an important dimension to evaluate the effectiveness of a policy. Our counterfactual results imply that policy makers should focus not only on the direct effect on the recipients of subsidies, but also on the indirect effect on the whole industries to determine the optimal policy.

Our research studies network structure and technology adoption in the setting of the Python programming language, a large OSS platform. Without explicit pecuniary rewards, it helps us to avoid other complications that comes with prices and focus instead on the pure effects of the network. We believe that our structural framework can be easily applied to study other industries where prices can be assumed to be fixed.

Undoubtedly, our model has many limitations to study a more general network. Ours heavily depends on the acyclicity property of the dependency relationships, whereas many networks can be cyclical. We also do not model the strategic interactions among agents, which can be of first-order importance in many settings. In that sense, our research raises more questions than it can answer. The answer to these more general questions requires not only high-quality data for one or multiple industries, but also the corresponding development of econometric modeling and estimation methods. As one of the first paper to link dynamic models and input-output networks, we hope that our work can contribute to further development in this direction.

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9 Online Appendix

9.1 Examples of Python 3 New/Incompatible Features

Python 3 offers many major improvements and new features compared to Python 2. Some are compatible to Python 2 and others aren't. The goal of this part of the appendix is not to give a comprehensive comparison between Python 2 and 3 but rather offer several examples to show the incompatibility between Python 2 and 3.

One of the most fundamental features that made Python 3 backward incompatible is the default encoding system, namely, the way Python deals with text.

In Python 2, like all the classic programming languages such as C, Fortran and Java, the encoding system is ASCII by default, which basically can only deal with English characters, puncutations, and digits that one can find on a standard English keyboard. Non-English characters have to be dealt in a more complicated way. For example, typing "café" in Python 2 gives an error: "ascii" codec can't decode. There are several solutions to deal with this issue but all require more advanced knowledge of the encoding system.

With the growing popularity of the Python programming language, especially among people who are new to programming, an easier way to deal with non-English characters has become one of the most requested features. Python 3 fundamentally changed its way of dealing with text by adopting Unicode as the default encoding system. With Python 3, "café" works perfectly well. However, much of the existing code in Python 2 fails to work, and many manual modifications need to be made.

Another fundamental change is division of integers. In Python 2, like all other major programmiing languages, the division sign "/" means floor division, e.g. $5/2 = 2$. Such behavior can be confusing for those new to programming. Python 3 changes it to behave more "naturally": $5/2 = 2.5$. The problem is that the old code in Python 2 works in Python 3 without errors but returns a different result.

9.2 Python Packages

As mentioned in Section 2, a package, in simple terms, can be defined as a collection of functions that anyone can use to finish more complex tasks. In this section, we provide a minimal example of Python code to illustrate what one can do with a package on Python.

A. Python Only	B. with package NumPy
A = [1,2,3]	import numpy
B = [1,1,0]	A = numpy.array([[1,2,3]])
result = 0	B = numpy.array([1,1,0])
for i in range(3):	A @ B
result = result + A[i] * B[i]	

To multiple two matrices $A = \left(\begin{smallmatrix}1\\2\\3\end{smallmatrix}\right)$ and $B = \left(1\,1\,0\right)$ with dimensions 3x1 and 1x3 respectively, one can do so with Python by creating two lists, loop through the two lists, and sum up the multiplied value, i.e. $1 \times 1 + 2 \times 1 + 3 \times 0 = 3$. Or one can use the NumPy package to first define two matrices and then multiply two matricies directly with $A@B$. The latter

method is more elegant, less error-prone, and more computationally-efficient, especially with large and multi-dimensional matrices.

9.3   Network Structure of Python Communities

(a) 0-database

(b) 1-cryptography

(c) 2-web development

(d) 3-web navigation

(e) 4-software development & text processing
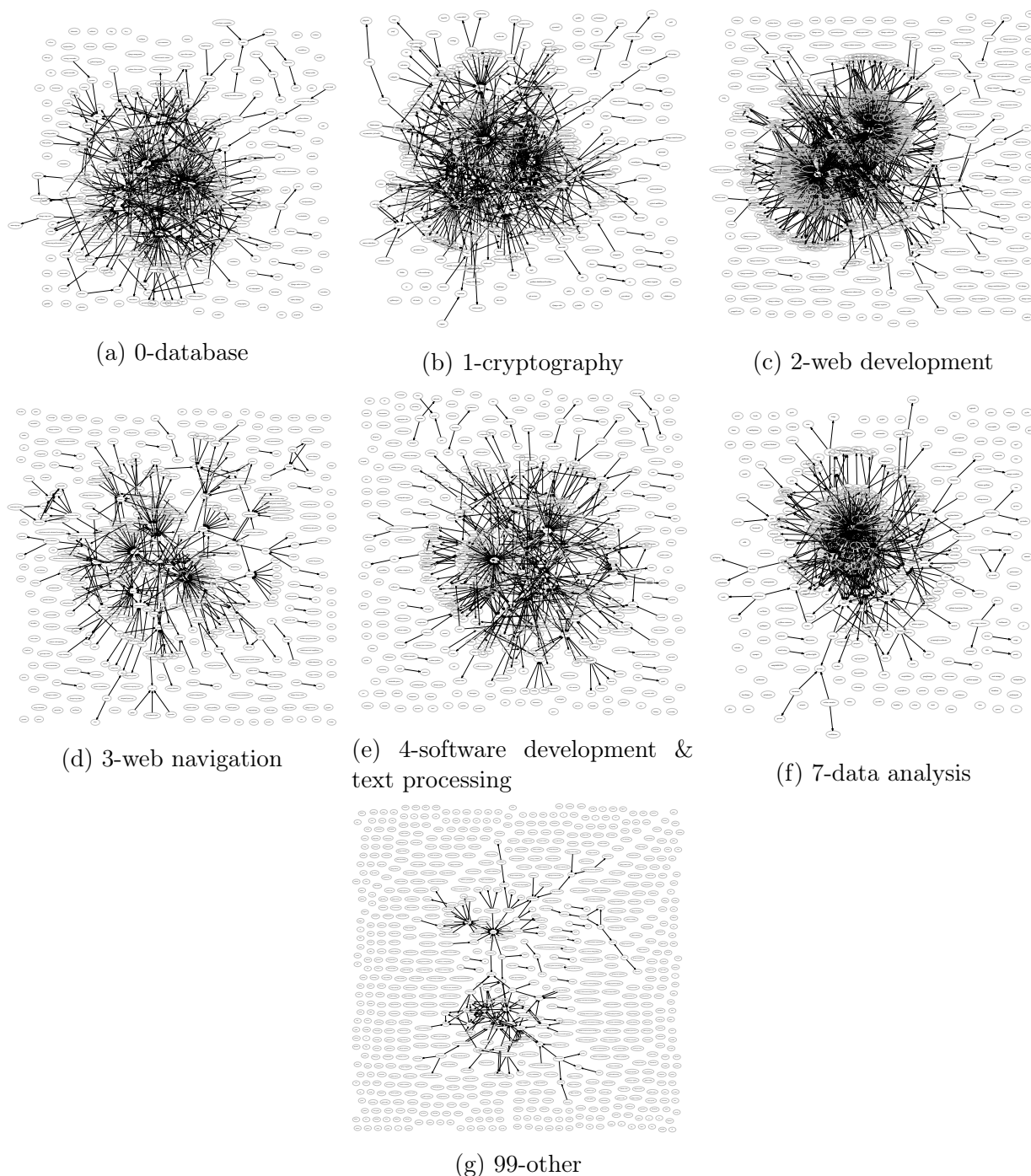
(f) 7-data analysis

(g) 99-other

Figure 11: Network Structure of Python Communities

9.4 More Results on Counterfactual

Table 7 reports the effectiveness of community-level cost subsidy three years after the policy. In this section, instead of list all the results across different years, we combine all the data together and seek some systematic pattern in the effects of the counterfactual policy. Moreover, we also measure the extent to which the prediciton from a nonlinear model can be captured by a linear one. We do so by running the following regressions:

$$\Delta r_{mt} = \gamma_0 + \gamma_1 Year_t + \gamma_2 Year_t^2 + \gamma_3 Density_m + \gamma_4 NumPackage_m + \gamma_5 AvgNumUpstream_m$$
$$+ \gamma_6 AvgNumDownstream_m + \gamma_7 AvgDownload_m + \gamma_8 AvgSize_m + \epsilon_{mt}$$
$$\Delta r_{m'mt} = \gamma_0 + \gamma_1 Year_t + \gamma_2 Year_t^2 + \gamma_3 Density_{m'm} + \gamma_4 NumPackage_m + \gamma_5 AvgNumUpstream_m$$
$$+ \gamma_6 AvgNumDownstream_m + \gamma_7 AvgDownload_m + \gamma_8 AvgSize_m + (FE_{m'}) + \epsilon_{mt},$$

where the dependent variables are defined as $\Delta r_{mt} = \widetilde{r}_{mt}$(subsidy on m)$-\widetilde{r}_{mt}$(without subsidy) and $\Delta r_{m'mt} = \widetilde{r}_{mt}$(subsidy on m') $- \widetilde{r}_{mt}$(without subsidy), respectively. Δr_{mt} measures the direct effect of subsidy on that community, and $\Delta r_{m'mt}$ measures the indirect effect of subsidy to m' on other communities m. Both are calculated as the differences between simulated adoption rate with and without the subsidy. The values of Δr_{mt} and $\Delta r_{m'mt}$ where t equals to year 3 correspond to the diagonal and off-diagonal values of Table 7. On the right-hand side of the equation, we control for some basic characteristics of a community. $Density_m$ measures the density of links within a community, and it's calculated as the number of actual links divided by the total number of potential links (all the possible combinations); $Density_{m'm}$ measures the density of links between two different communities, and it's calculated as the number of links originating from packages in community m' to those in community m, divided by the number of potential links. $NumPackage_m$ represent the total number of packages in the affected community; $AvgDownload_m$ and $AvgSize_m$ are the log value of average downloads and size in the affected community.

The regression results are reported in Table 9. Note that the goal here is not to establish causal inference but rather to detect systematic patterns between community characteristics and effects from counterfactual policies, as well as to test how well a linear model captures variations generated from a structural model. In Panel A, The network density measure is not statistically significant. However, the variations of the effects for different communities are well captured by the whole linear model (R^2 around 70%). In Panel B, column 3nad 4 indicate a positive correlation between network density and the effect on a community, i.e. if two communities are densely connected, then subsidy to one community is also more likely to have a larger effect on the other one. However, the estimates after controling for fixed effects of the targeted community m' seem to suggest such effects doesn't exist, and the aforementioned effects are likely coming from differences across the targeted communities instead of differences in the across-community densities. Note that the R^2 is rather small (16.5% even with the community-level fixed effects). These results indicate though a linear model can well capture the variations of the direct effect, it fails to capture the indirect effect—namely, the effect that a policy has on other connected communities. These indirected can be large, as discussed in Section 7 and should be considered by policy makers in order to maximize the effectiveness of a promotion policy.

Table 9: Evaluation of Community-Level Subsidy by Linear Model

	A: Within-Community		B: Across-Community		
	(1) Δr_{mt}	(2) Δr_{mt}	(3) $\Delta r_{m'mt}$	(4) $\Delta r_{m'mt}$	(5) $\Delta r_{m'mt}$
Density_m	0.006	-0.025			
	(0.05)	(0.07)			
$\text{Density}_{m'm}$			0.094***	0.062*	-0.052
			(0.03)	(0.03)	(0.06)
NumPackage_m		0.000		0.000***	0.000***
		(0.00)		(0.00)	(0.00)
AvgDownload_m		0.003		0.004***	0.004***
		(0.00)		(0.00)	(0.00)
AvgSize_m		0.011**		0.004***	0.004***
		(0.01)		(0.00)	(0.00)
Year_t	0.012***	0.012***	-0.000	-0.000	-0.000*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year_t^2	-0.001***	-0.001***	0.000**	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.057***	-0.042	-0.001***	-0.069***	-0.072***
	(0.00)	(0.07)	(0.00)	(0.01)	(0.01)
FE_m					x
N	119	119	714	714	714
R^2	0.699	0.725	0.032	0.141	0.165

37