Technology Adoption in Dependency Networks: A Study of the Python Programming Language

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Abstract

This paper studies how network structure can affect the speed of adoption. In particular, we model the decision 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 dependency networks through dependency relationships with other packages, and they face an 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 packages. Estimation results show that the average cost of one incompatible dependency is roughly three times the cost for updating one's own code. We conduct several counterfactual policies of targeted community-level promotion. The results show significant heterogeneous effects across communities and the role of the dependency network changes as packages become more interlinked. Moreover, we find packages have more incentive to free ride by delaying adoption if dependencies are more likely to adopt.

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1 Introduction

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)). This paper demonstrates how the speed of the adoption can be affected by dependency networks and how targeted promotion policy can be used to facilitate a faster adoption process in an dependency network.

We study this issue in the context of the Python programming language, in particular, the transition from Python version 2 to version 3.[1] Python is one of the most popular programming languages in the world. Python 3 was a major release in 2008 that experienced slow adoption.[2] It provides several fundamental improvements but is *incompatible* with Python 2.[3] 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 dependency networks through dependency requirements: downstream packages are built using functionalities provided by upstream packages, or upstream packages are dependencies for downstream packages.[4] To use a package, the end user must install the package itself, as well as all of its upstream dependencies.[5]

Our research focuses on the decision to adopt Python 3 made by third-party packages. Deciding to adopt 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 any of their upstream dependencies have yet to adopt Python 3, additional development efforts must be made; that is, a higher adoption cost.[6]

Unlike other industries with dependency networks, there is no explicit pecuniary compensation in open-source software (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 OSS (e.g., altruism, career incentives, ego gratification), more

[1] Similar issues exist in other software or programming languages, such as Windows dynamic-link libraries (DLLs), Fortran, and Ruby. We study Python mainly due to data availability.

[2] The Python 3 adoption process has been widely considered slower than optimal.

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

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

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

[6] 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.

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), Keane and Wolpin (1997), and Aguirregabiria and Mira (2010). 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 may 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. This has created significant computational challenges to our estimation.

With a complete dataset of package characteristics, historical releases and user download statistics, we draw the dependency network of packages.[7] To deal with the computational burden, we propose a novel estimation procedure that takes advantage of the dependency relationship among packages. We group packages into various layers based on the dependency network 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 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 Python programming language is managed by a non-for-profit organization named Python Software Foundation (PSF). PSF oversees all the major issues related to Python, including the transition from Python 2 to Python 3. To maintain a smooth and rapid transition has been one of the top priorities of PSF, because such transition to a new standard can be difficult and might lead to disastrous results if not well managed.[8]

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 subsidies to adopt Python 3. We use modularity optimization tools developed in the social network literature to group the packages into various "communities" based on the dependency network: for example, web development and data analysis communities. These communities have very different network structures, which also evolve over time. Packages are more densely linked within a community but less so across different communities. Through counterfactual simulation, we show how

[7]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.

[8]For example, in the case of the Perl programming language, the transition from Perl 5 to Perl 6 was widely considered as a failure and painful process for developers.

technology adoption decisions can propagate 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 have significant positive or negative effects on connected communities. As more packages become available and are more interlinked, the dependency network becomes a larger obstacle to the adoption speed. We also explore the optimal policy to maximize the effectiveness of cost subsidies to promote a faster Python 3 adoption. The findings imply that policies that consider network structure can significantly improve the effectiveness of promotion.

This paper contributes to several literatures. It contributes to the literature of technology adoption by demonstrating a new channel through which the speed of adoption can be affected. The rich literature on technology adoption shows that many factors can slow the speed of adoptions; for example, organization (Atkin et al. (2017)), competition (Gowrisankaran and Stavins (2004)), demand conditions (Macher, Miller and Osborne (2020)), and network effects (Saloner and Shepard (1995)).[9] To the best of our knowledge, this paper is the first to measure such adverse effects of dependency networks on technology adoption.

This paper also contributes to the emerging literature that links network analysis and technology adoption. Previous papers on network effects 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.[10] Recent literature start to consider more detailed linkages between individual agents on a network. Ryan and Tucker (2011) measures the heterogeneous network effects from adopting a video-calling technology within a company. Compared to their study, our model allows for richer heterogeneity patterns across individuals. Apart from differences in individual characteristics, we also consider the detailed linkages among packages and allow them to discount future utilities differently. By imposing a functional form, we use several package characteristics that can potentially affect how package developers value future downloads to capture heterogeneity in the discount factor. On the other hand, the literature of social networks has always considered the detailed linkages between individuals, but with limited dynamics. Individuals in reality are inherently dynamic and face intertemporal trade-offs, and 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)). Bjorkegren (2018) is one of the first attempts to model technology adoption in a complex network and studies the adoption of mobile phones in Rwanda through the calling network. Bjorkegren (2018) circumvents the complex dynamic problem by solving per-period equilibria of optimal timing to adopt, and assumes that each individual makes the adoption decision with full knowledge of the actual future adoption time of her contacts. Our approach is based on the dynamic discrete choice

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

[10]Early seminal work includes Farrell and Saloner (1985) and Katz and Shapiro (1986). A more recent overview of the literature can be found in Cabral (2011)

model. In this model, individuals decide whether or not to adopt a new technology in the current time period, instead of when to adopt a new technology in a future time period. Agents predict the future adoption probabilities based on the current states. Our approach relaxes the perfect foresight assumption of other agents' fugure adoption decisions, though other simplifying assumptions are needed for the estimation.

Last, our research contributes to the growing marketing literature that evaluates the impacts of network structure on peer decisions. Generally speaking, a major difference is the role of dynamics in modeling choices. Models of social networks tend to have complex structures to explain the interaction among individuals but have little dynamic component. With a relatively simpler network structure, our paper can accommodate agents' forward-looking behavior. Hu, Yang and Xu (2019) explores the effects of social learning on wireless carrier decisions through a dynamic structure model with interpersonal interactions. Max Wei (2020) studies how film producers position their films to maximize box office receipts by comparing them to other network peers through a network formation model. Similar to these two papers, we also emphasize the importance of an agent's "position" in their network. That is to say, an agent occupying a centralized position has greater influence on peers on the network. The main difference comes from the nature of the network studied. The dependency network in our study is hierarchical in the sense that one agent relies on the decision of another agent, but not the other way around. This feature allows us to model the rich dynamics when an agent makes the adoption decision. In a more recent paper, Grewal, Lilien and Mallapragada (2006) studied the herding effect of advertising expenditure disclosure by peer firms and benchmark leaders in the network. Our paper provides an alternative dynamic structural approach to evaluate the effects of decisions made by other agents in the network.

2 Background: The Python Programming Language

Python is a general-purpose programming language.[11] It has a syntax that allows users to express concepts in fewer lines of code compared with most other major programming 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.[12] In the past few years, Python has become one of the most popular programming languages.[13]

Backward compatibility has been a widely disputed topic in the software industry.

[11] 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).

[12] There are no backward compatibility issues from Python 1 to Python 2.

[13] For example, based on the number 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 number one since 2018.

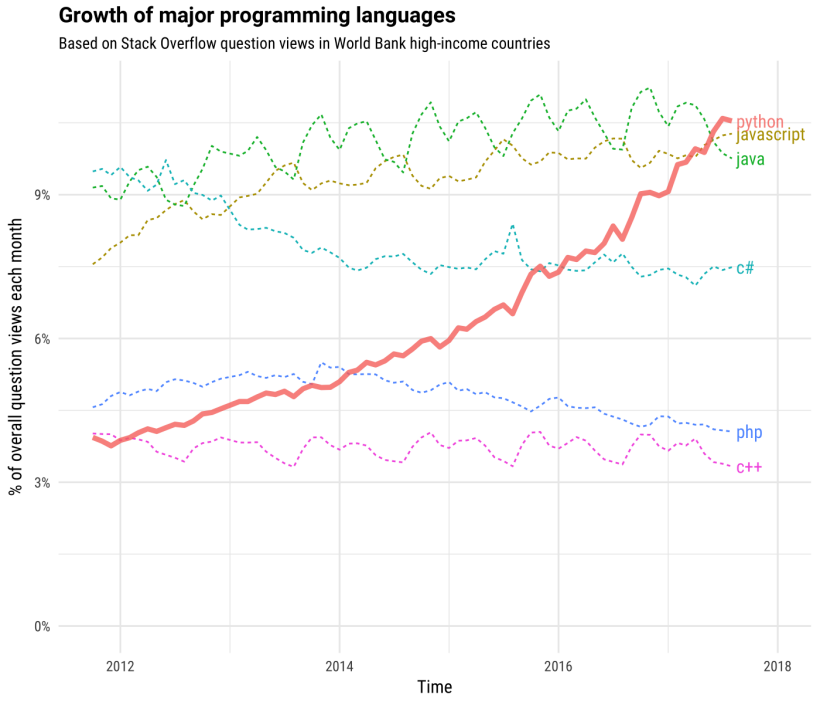


Figure 1: Popularity Trend of Programming Languages

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 trade-off is clear: easier user transition to new technology versus a higher cost of development and slower innovation. Users and package developers who want to run their code on Python 3 have to update all of the source code to be compatible with Python 3.[15]

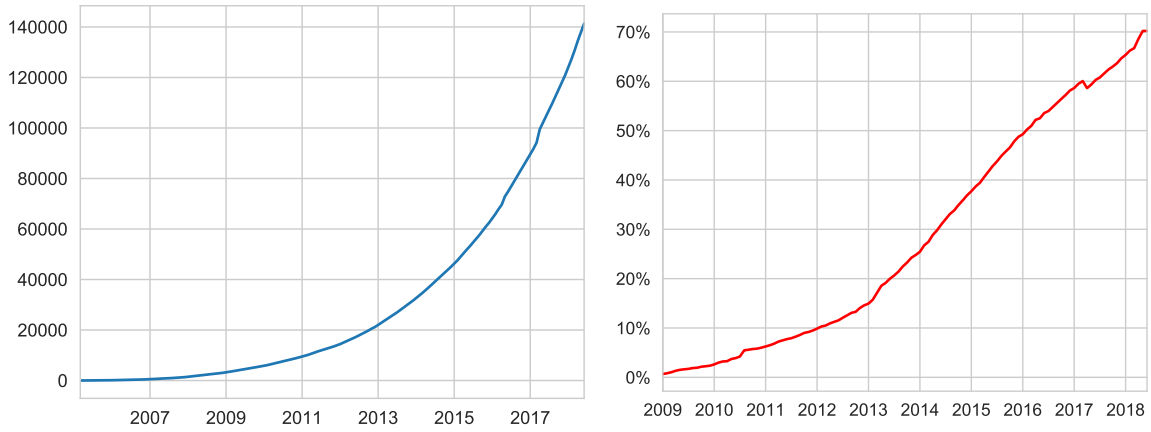
Most functionalities on Python are provided by third-party packages. In simple terms, packages can be viewed as a collection of tools and functions that anyone can use to work on more complicated tasks.[16] Packages are also known as libraries, modules, and (sub)routines in other programming languages.

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

[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 Appendix 10.1.

[15]Some packages are developed to help users to transition more easily to Python 3 through automation. However, in most cases, users and package developers still have to test and manually modify much of the code.

[16]A more accurate description and definitions of packages can be found in the official Python documentation at `https://docs.python.org`. Appendix 10.2 also provides a simple example to show how a package is used.



(a) Total Number of Packages

(b) % of Packages with Py3 Support

Figure 2: Python Packages with Python 3 Support

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 a significant number of 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 OSS.[17] The motivations for OSS contributions 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, and ego gratification.

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, while *SciPy* provides more applied tools used in science, such as linear regression, which requires 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 packages first.

Figure 3 shows a small section of the dependency network of Python packages. The

[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 require payment for usage.

[18]von Krogh et al. (2012) and Xu, Nian and Cabral (2020) provide overviews of the literature.

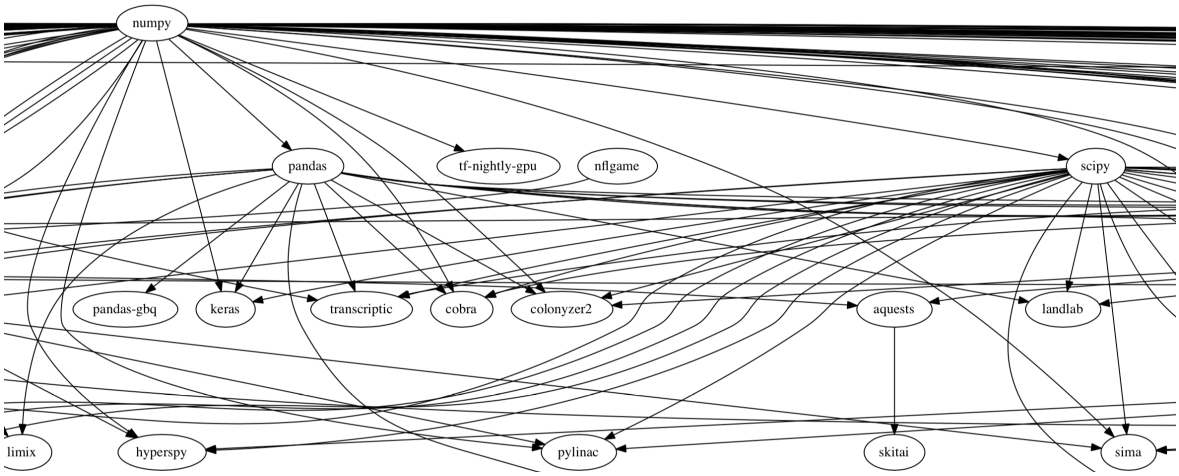


Figure 3: Sample Dependency Network of Python Packages

arrows represent the dependency relationship.[19] For example, an arrow from *NumPy* to *SciPy* means *NumPy* is the dependency of *SciPy*. 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 for and download the packages they need.

When uploading packages to PyPI, package developers usually provide various kinds of information related to the files, such as the description of the package, the contact information for the owners, whether they provide support for Python 2 or Python 3, and what other packages are required as dependencies. [20]

User downloads data consists of two separate sources recorded by PyPI. Before 2016, cumulative download statistics for each file were recorded (Table 2(a)). The system stopped working for a few months from January to May 2016, when PyPI introduced a new system hosted on Google BigQuery. The new system records and publishes certain information related to each individual download (Table 2(b)). We combine the

[19]In principle, the whole dependency network is acyclical. In other words, a circular dependency relationship such as $A \to B \to C \to A$ is not supposed to exist. In the data, there exist a negligible number of cases of circular dependencies (47 out of 90,551 links). We compare the characteristics of all package pairs and manually remove the most "unlikely" link, measured by the number of times a package is used as a dependency.

[20]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

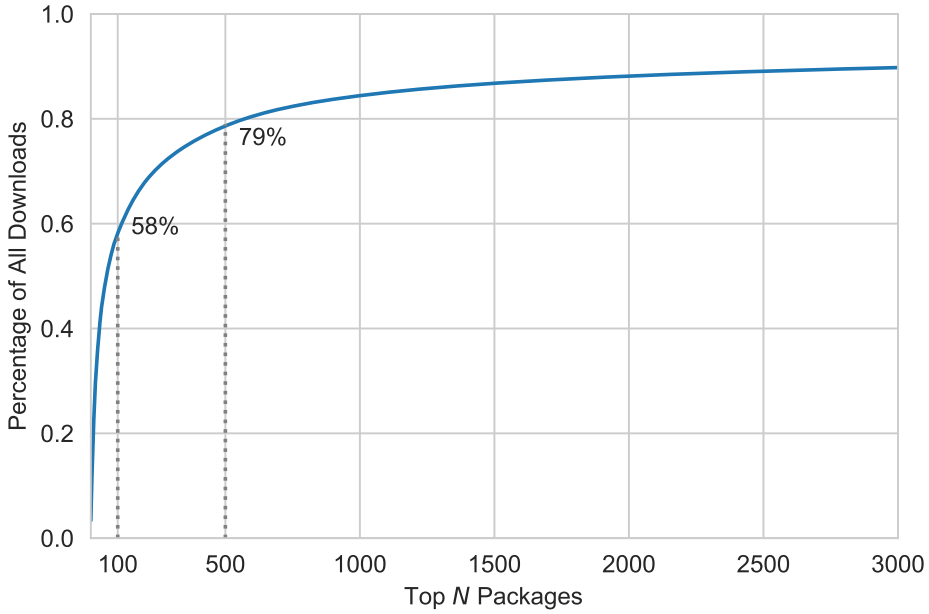


Figure 4: Total Downloads of Top Packages as Percentage of All Downloads

two sources of user downloads data and extrapolate the number of downloads for the missing time periods from January to May 2016. [21]

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. User downloads are concentrated on a relatively few number of popular packages. In 2017, the top 100 packages account for approximately 58% of all downloads, and the 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%)
- Total Number of Releases $\geq$ 5 (38.9%)
- Total Releases / Time Duration $\geq$ 1 (92.4%)
- Some Python 2/3 Support Information Available (59.9%)

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

[21] Competing platforms to PyPI also exist. The most popular one is Anaconda. All packages on Anaconda are also hosted on PyPI but the user downlaods data are not publicly available. Anecdotal evidence indicate Anaconda holds a relatively small market share throughout our data period.

Table 3: Summary Statistics

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

Column "All": all packages available on PyPI at the time of data collection (2018); Column "Selected": selected packages used for estimating the model; Column "Dep ≥ 1": those with more than one dependencies among the selected packages.

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 of 46.40% 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 2.27 dependencies versus 0.07 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 an 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.[22][23] Let

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

[23]One potential violation to model assumption is that some packages share the same set of contributors. In our data, 84.3% of package authors have 1 package, and 10.9% have 2 packages. We don't think this is a major concern that can significantly affect the model estimation.

$d_{i,t}$ be a binary irreversible decision:[24]

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

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:

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

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 the dependencies of dependencies, etc. One implicit assumption embedded in this nested state variable is a sequential move assumption, meaning that package i observes the adoption decision made by its dependencies before making its own adoption decision. Section 4.3 provides more discussion and implications of 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:

$$\begin{aligned} & u(S_{i,t}, d_{i,t}; \theta) - C(S_{i,t}, d_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}} \\ =& u(S_{i,t}, d_{i,t}; \theta) - \mathbf{1}(d_{i,t-1} = 0, d_{i,t} = 1)\, C(S_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}}, \end{aligned} \tag{2}$$

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:

$$V_\theta(S_{i,t}, d_{i,t-1} = 0) \tag{3}$$

[24] 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 ($d_{i,t+\tau} = 1 \quad \forall \tau \in N$).

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

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

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

$$\begin{aligned} & V_\theta(S_{i,t}, d_{i,t-1} = 0) \\ =& \max_{d_{i,t} \in \{0,1\}} u(S_{i,t}, d_{i,t}; \theta) - d_{i,t}\, C(S_{i,t}; \theta) + \nu_{i,t}^{d_{i,t}} + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t}) \\ =& \max\{v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 0),\ \ v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 1)\} \\ =& \max\{u(S_{i,t}, d_{i,t} = 0; \theta) + \nu_{i,t}^0 + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 0), \\ & \quad u(S_{i,t}, d_{i,t} = 1; \theta) - C(S_{i,t}; \theta) + \nu_{i,t}^1 + \beta_i \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 1)\}. \end{aligned} \tag{4}$$

The representation of value function for packages with Python 3 support is more straight-forward because the irreversibility condition implies that no further decisions are being made:

$$\begin{aligned} & V_\theta(S_{i,t}, d_{i,t-1} = 1) \\ =& v_\theta(S_{i,t}, d_{i,t-1} = 1, d_{i,t} = 1) \\ =& \mathbf{E}_t\{\sum_{\tau=0}^{\infty} \beta_i^\tau \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big) | S_{i,t}; \theta\} \\ =& \sum_{\tau=0}^{\infty} \beta_i^\tau \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big) dF_\theta(S_{i,t+1} | S_{i,t}). \end{aligned} \tag{5}$$

We assume that $\nu_{i,t}^{d_{i,t}}$ 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:

$$\begin{aligned} & \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 0) \\ =& \int V_\theta(S_{i,t+1}, d_{i,t} = 0) dF_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 0) \\ =& \int \log\{\sum_{d_{i,t+1} \in \{0,1\}} \exp(v_\theta(S_{i,t+1}, d_{i,t} = 0, d_{i,t+1}))\} dF_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 0) \end{aligned} \tag{6}$$

$$\begin{aligned} & \mathbf{E}_t V_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 1) \\ =& \int V_\theta(S_{i,t+1}, d_{i,t} = 1) dF_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 1) \\ =& \sum_{\tau=1}^{\infty} \beta_i^{\tau-1} \int \Big(u(S_{i,t+\tau}, d_{i,t+\tau} = 1; \theta) + \nu_{i,t+\tau}^1\Big) dF_\theta(S_{i,t+1} | S_{i,t}, d_{i,t} = 1). \end{aligned} \tag{7}$$

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:

$$P(d_{i,t} = 1|S_{i,t}, d_{i,t-1} = 0; \theta) = \frac{v_\theta(S_{i,t}, d_{i,t-1} = 0, d_{i,t} = 1)}{\sum_{d' \in \{0,1\}} v_\theta(S_{i,t}, d_{i,t-1} = 0, d')} \tag{8}$$

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

$$P(d_{i,t} = 1|S_{i,t}, d_{i,t-1} = 1; \theta) = 1 \tag{10}$$

$$P(d_{i,t} = 0|S_{i,t}, d_{i,t-1} = 1; \theta) = 0. \tag{11}$$

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 and Gandal (2008)), we model the payoff of package developers as a function of user downloads. Denote $x_{i,t}$ as the logarithm of the 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:

$$u(S_{i,t}, d_{i,t}; \theta) = \alpha^x \, x_{i,t}(x_{i,t-1}, d_{i,t}; \theta). \tag{12}$$

Furthermore, we assume that the evolution of the demand follows a first-order Markov process:[25]

$$x_{i,t} = \rho_i + \rho_1 \cdot x_{i,t-1} + \rho_2 \cdot ds_{i,t} + \rho_3 \cdot d_{i,t} \cdot r_t + \epsilon_{i,t}, \tag{13}$$

where d indicates a package i's adoption status/decision $d_{i,t}$; $ds_{i,t}$ is the number of packages that specify i as their dependency package, that is, the number of i's downstream packages; r_t is the current Python 3 adoption rate among all packages; ρ_i is the fixed effect for each package i; and $\epsilon^0_{i,t}, \epsilon^1_{i,t}$ are two white noises that are normally and independently distributed with mean 0 and variance σ^2_ϵ.[26]

There are several elements of heterogeneity captured in the model apart from the unobserved error terms. The first one is the fixed effects ρ_i. It captures heterogeneity in popularity and underlying motives of package development.[27] The second heterogeneity comes from user downloads. Note that the download variable $x_{i,t}$ is in logarithm terms. A change in other terms would translate to different levels of downloads with different

[25] The previous Working Paper versions have adopted a slightly different demand process without fixed effects. The results do not change qualitatively.

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

[27] For example, some packages are hobby projects without regular maintenance, and others can be serious software development with a larger team behind it.

popularity. For example, a package with a large existing Python 2 user base is also more likely to have a significant additional number of potential users on Python 3. The adoption by an important package with many downstream packages may cause a cascade effect for many others, and such a package itself also benefits from the direct downloads from it. The third heterogeneity lies in the temporal dimension.Adoption benefits change over time and are reflected mainly through the $d_{i,t} \cdot r_t$ term. 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 downloads because package developers have no more download statistics than econometricians. Lastly, the parsimonious first-order Markov process can well capture the variations of downloads in the data (see Section 7).

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 defined as below:

$$C_{i,t} = c_0 + \alpha^{\mu}\, \mu_{i,t} + \alpha^{s}\, s_{i,t}, \tag{14}$$

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

$$\mu_{i,t} = \sum_{j \in U_i} \mathbf{1}\{d_{j,t} = 0\}\, s_{j,t}, \tag{15}$$

meaning the number of incompatible dependencies is weighted by package sizes. We prefer this to the raw number of dependencies because, in reality, the cost to deal with an incompatible dependency may 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 captured by $\mu_{i,t}$ and $s_{i,t}$. One important component is the difference between Python 2 and 3, or the difficulty level for a developer to learn Python 3. Since it is a one-time cost, c_0 also includes the present value of future maintenance costs.

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

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 is 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 for the following reasons. First, upstream packages tend to be the more popular ones that often pre-announce their plans for future releases, including the Python 3 adoption decision. 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 that 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 will be specified in detail in Section 6.1.

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.[28]

Assumption 2. *A package* i *does not explicitly consider responses from its downstream packages* k *where* $\mathrm{i} \in \mathrm{U_{k,t}}$.[29]

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.[30] 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 other words, it is likely that indirect downloads through downstream packages account for a

[28]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.

[29]In Section 5.1, we relax Assumption 2 by allowing each package to predict the adoption decisions of its downstream packages. More details can be found in Section 5.1.

[30]For example, a package might receive much of its downloads indirectly through a popular downstream package, thus having stronger incentive to adopt Python 3 earlier due to the fear of being dropped as a dependency. Such strategic interactions are not explicitly modeled, but the effects are implicitly approximated in the first-order Markov process.

small portion of total user downloads.[31] Moreover, an upstream package often has many downstream packages and is unlikely to track all the downstream packages dependent on it.

4.4 State Variables and 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 $\{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}$ insofar 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:

$$\begin{aligned} & \mathbf{P}(\mu_{i,t+1} = \mu' | \mu_{i,t} = \mu, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}; \theta) \\ = \ & \mathbf{P}(\mu' | \mu, \{d_{j,t}, S_{j,t}\}_{j \in U_{i,t}}; \theta), \end{aligned} \tag{16}$$

where $\mu \geq \mu'$, meaning 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 16 as:

$$\mathbf{P}(\mu' | \mu, \{\widehat{p}_{j,t+1}\}_{j \in \Omega_{i,t}}; \theta). \tag{17}$$

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 simplified as:

$$\begin{aligned} & \mathbf{P}(o' \mid \Omega_{i,t}, \{\widehat{p}_{j,t+1}\}_{j \in \Omega_{i,t}}; \theta) \\ = \ & \prod_{j \in o'} \widehat{p}^0_{j,t+1} \prod_{j \in \Omega_{i,t} \setminus o'} \widehat{p}^1_{j,t+1}, \end{aligned} \tag{18}$$

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

[31] Unfortunately, neither the econometrician nor the packages have a clear knowledge regarding the portion of downloads coming from direct versus indirect channels. The data limitation is another reason why we make such an assumption.

4.5 Transition Matrix

The calculation of EV in equation 7 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 13, with the parameter values estimated outside of the value function iteration. In contrast, the law of motion of $\mu_{i,t}$ is much more difficult.

One of the most important trade-offs for package i to adopt Python 3 today at t versus 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 $t+1$:

$$\widehat{p}^{1}_{j,t+1} = \int_{S_{j,t+1}} \mathbf{P}(d_{j,t+1} = 1 | S_{j,t+1}, d_{j,t} = 0, z_j; \theta) d\mathbf{P}(S_{j,t+1} | S_{j,t}, d_{j,t} = 0, z_j; \theta). \quad (19)$$

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

$$\widehat{p}^{1}_{j,t+1} = \frac{1}{M} \sum_{m=1}^{M} \mathbf{P}(d_{j,t+1} = 1 | S^m_{j,t+1}, d_{j,t} = 0, z_j; \theta). \quad (20)$$

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 Section 6, we list the detailed steps outlining how to compute $p_{j,t}$ for $j \in \Omega_{i,t}$ given the dependency 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 $\widehat{p}^{1}_{j,t+\tau}$ for each of $j \in \Omega_{i,t}$ and $\tau \in \mathbb{N}$.

Given the transition probability specified in equation 18, the full transition matrix needed to calculate $EV(S, d = 0; \theta)$ can be specified as the following:

$$P(o' \in O_{i,t} | o \in O_{i,t}) = \begin{cases} 0 & \text{if } o \nsubseteq o' \\ \prod_{j \in o'} \widehat{p}^0_{j,t} \prod_{j \in o \setminus o'} \widehat{p}^1_{j,t} & \text{if } o \subseteq o' \end{cases}. \tag{21}$$

The calculation of the transition matrix, as specified in equation 21, 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 $\widehat{p}^1_{A,t+1} = a$ and $\widehat{p}^1_{B,t+1} = b$. The powerset of $\Omega_{i,t}$ is $\mathcal{O}_{i,t} = \{\varnothing, \{A\}, \{B\}, \{A, B\}\}$, and $\mathcal{O}^0_{i,t} = \{\varnothing\}$. Therefore, the transition matrix of μ can be calculated using equation 21:

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

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 that matter for the optional value of waiting for package i. The transition matrix calculated using equation 21 considers all such cases.

5 Model Extensions

5.1 Relaxing Assumption 2

With Assumption 2, a package i does not explicitly consider decisions of its downstream packages. In theory, the decisions of downstream packages matter because it would affect the downloads a package would receive (equation 13). Though it's unlikely to be the case in reality due to the large number of downstream packages and there is no systematic way for a package to know who are the downstream packages nor where the downloads come from, the assumption can be very restrictive from a modeling perspective. In this section, we relax Assumption 2 by allowing a package i to predict decisions of its downstream packages.

In the baseline model, $ds_{i,t}$ was treated as an exogenous variable taken directly from the data. Here we endogenize $ds_{i,t}$ in the adoption model by allowing each package i to predict changes of $ds_{i,t}$ as a result of its own adoption decision $d_{i,t}$.

Denote the set of downstream packages as $D_{i,t} = \{k|i \in U_{k,t}\}$, that is to say, all packages k that use i as dependency. Then we assume package i predicts changes of its number of downstream packages in the following way:

$$ds_{i,t}(d_{i,t}) = \begin{cases} ds_{i,t-1} & \text{if } d_{i,t} = 1 \\ ds_{i,t-1} - \sum_{k \in D_{i,t}} p^1_{k,t}(d_{i,t} = 0) & \text{if } d_{i,t} = 0 \end{cases}$$

The increase in computational burden from endogenizing $ds_{i,t}$ can be astronomical, due to an exponential increase in state space from the interdependency relationship between upstream and downstream packages. To avoid the computational burden, we adopt the ideas proposed by Dube, Hitsch and Chintagunta (2010) and Ryan and Tucker (2011) which stems from Bajari, Benkard and Levin (2007) but with slightly stronger conditions to estimate dynamic games: We assume each package i do not perfectly predict the evolution of $ds_{i,t}$ but rather approximate the value by using a parsimonious logit function to calculate $p^1_{k,t}(d_{i,t} = 0)$. In particular, $p^1_{k,t}(d_{i,t} = 0)$ is approximated by a logit function that is estimated outside of the structural model in the following way:

$$\widetilde{p}^1_{k,t}(d_{i,t} = 0) \approx p^1_{k,t}(d_{i,t} = 0) = \frac{\exp\left(\delta_0 + \delta_1 x_{k,t} + \delta_2 \mu_{k,t}(d_{i,t} = 0) + \delta_3 s_{k,t}\right)}{1 + \exp\left(\delta_0 + \delta_1 x_{k,t} + \delta_2 \mu_{k,t}(d_{i,t} = 0) + \delta_3 s_{k,t}\right)}$$

Another simplifying assumption here is package i's has a myopoic belief of future evolutions of $d_{i,t}$, that is to say, package i predicts the change of $ds_{i,t}$ due to its own adoption decision $d_{i,t}$ and we assume $ds_{i,t'} = ds_{i,t} \forall t'$.

Then, in the structural adoption model, $ds_{i,t}$ now becomes $ds_{i,t}(d_{i,t})$, and if $\rho_3 > 0$ in equation 13, then we should expect $ds_{i,t}(d_{i,t} = 1) \geq ds_{i,t}(d_{i,t} = 0)$. That is to say, if package i doesn't adopt Python 3, then some of its downstream packages might adopt Python 3 and drop package i as a dependency. In this case, package i's number of downloads would also be affected due to a smaller number of $ds_{i,t}$.

5.2 Heterogeneous Discount Factor

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

$$\beta_i \equiv \mathcal{B}(z_i'\lambda) = 1 - e^{-e^{z_i'\lambda}} \tag{22}$$

$$\begin{aligned} \text{where } z_i'\lambda = \lambda_0 &+ \lambda_1 \, Releases_i + \lambda_2 \, Files_i \\ &+ \lambda_3 \, Description_i + \lambda_4 \, Classifiers_i. \end{aligned} \tag{23}$$

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;[32] $Description_i$: average number of characters used in the description section; and $Classifiers_i$: average number of classifiers (similar to tags or labels) associated with each package.[33]

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.

6 Identification and Estimation

The parameters of interest in our model are the following:

$$\theta = \{\underbrace{\rho_0, \rho_1, \rho_2, \rho_3, \rho_4, \rho_r}_{\theta_D}; \underbrace{c_0, \alpha^\mu, \alpha^s, \beta}_{\theta_S}\}.$$

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 structural model of technology adoption by package developers.

6.1 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 the reason mentioned in 4.2.[34]

One major concern is that the estimates of the AR(1) process may suffer from an endogeneity problem. The AR(1) 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 AR(1) estimates can be over-exaggerated. To correct the

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

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

[34]See Hollenbeck (2017) for similar separate estimation combining reduced-form and structural models of demand and supply.

endogeneity problem, we instrument the adoption decision $d_{i,t}$ using package characteristics including the number of incompatible dependencies and package size.[35][36]

Then the estimates of the AR(1) 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 (2019)). In theory, such variations can be found in our data: imagine a case where two packages, A and B, that are identical in every way except for their dependencies are the same size. In this case, A and B also face identical adoption costs 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 affect the optional value of waiting for A and B. In practice, however, there are very few cases, and the identification power from this source is rather weak.[37]

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-offs 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 a slight difference in user downloads. Assume that the initial differences in downloads also lead to persistent long-term differences. If such small differences lead to large discrepancies 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 the current period's utility per unit of download.

[35]The validify of the instrument variables hinges on the assumption that the instruments affect the cost of adoption, but they do not affect the number of downloads in channels other than the Python 3 adoption decision.

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

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

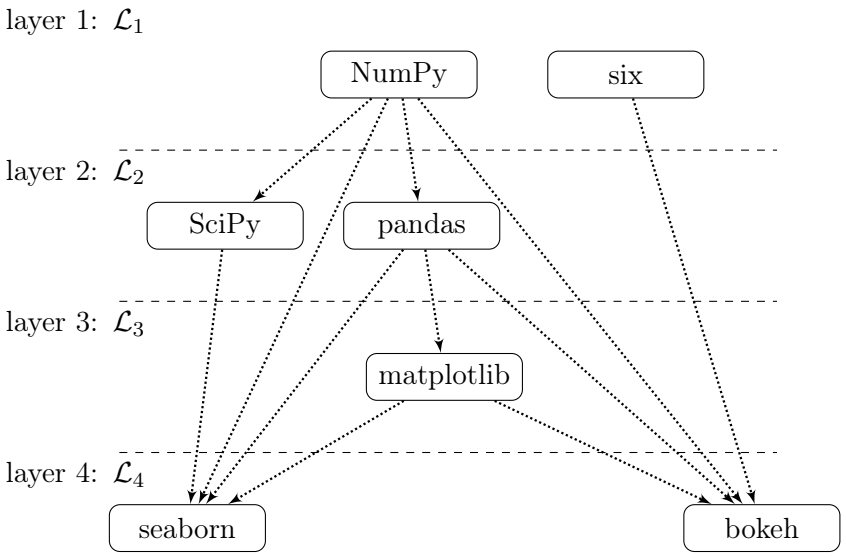


Figure 5: Example of the Layered Network Representation

6.2 Estimation Method

Our model of technology adoption is estimated using the 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 8.

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.[38] 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.

[38] 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. Such cases comprise a small percentage of cases in the data.

In every time period t, packages in layer 1 decide to adopt Python 3, followed by those in layer 2, then those in layer 3, ..., etc. The probability of adopting Python 3 for each of the upstream packages is then used for the decision-making process of the downstream package, in order to calculate the transition probability of $\mu_{i,t}$.

The construction of the state variable requires knowledge of adoption probability of all of one's dependencies. The layered estimation approach helps calculate all necessary inputs before solving each package's dynamic problem. It's helpful to start with packages in layer 1 where packages do not have dependencies. For a package $i \in \mathcal{L}_1$ at time t, the adoption probability $\widehat{p}_{i,t}$ can be calculated by solving the dynamic problem which requires a transition matrix involving the evolution of the number of downloads $(x_{i,t})$. Say the package i decides not to adopt. Although the likelihood calculation only requires $\widehat{p}_{i,t}$, it's convenient to calculate $\widehat{p}_{i,t'}$ where $t' = t+1, t+2, ...$ These adoption probabilities are useful when solving a downstream package's dynamic problem. For another package $k \in \mathcal{L}_1$ at time t, the dynamic problem we need to solve requires a transition matrix involving both the evolution of the number of downloads $(x_{k,t})$ and the weighted number of incompatible-dependencies $(\mu_{k,t})$, because package k needs to predict how $\mu_{k,t}$ evolves in the future. With the adoption probabilities of its dependency $\widehat{p}_{i,t'}$ already calculated, we can conveniently construct the transition matrix following the steps in Section 4.5.

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 come from the estimation of the AR(1) process of user downloads, specified in equation 13. Estimation then involves iteration on the four steps, where the m^{th} iteration follows.

Step 1: Estimate Demand Parameters θ_D Using IV

- Estimate the first-order Markov process of demand function using $\mu_{i,t}$ and $s_{i,t}$ as IV for $d_{i,t}$ (equation 13).

Step 2: Estimation of the Model of Technology Adoption

- Given the 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 $\widehat{p}^1(S_{i,t};\theta)$

  $\vdots$

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

7 Results

7.1 Model Estimation

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

	(1) OLS	(2) IV
$x_{i,t-1}$	0.511***	0.568***
	(0.01)	(0.01)
$ds_{i,t}$	0.326***	0.384***
	(0.02)	(0.02)
$d_{i,t} \times r_t$	0.771***	0.158***
	(0.03)	(0.03)
Constant	4.566***	4.211***
	(0.08)	(0.02)
N	46476	46476
R^2	0.714	0.730

Note: First-stage regression results indicate the instruments are not weak. Overidentification test (Hansen J test) shows a p-value of 27%.

Table 4 summarizes the parameter estimates of the download process, modeled as a first-order Markov process specified in equation 13. Column 1 shows results from OLS regression and column 2 corrects the endogeneity of $d_{i,t}$ as explained in Section 6.

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 $ds_{i,t}$) may find that Python 3 adoption negatively affects the number of downloads. It is likely to be 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

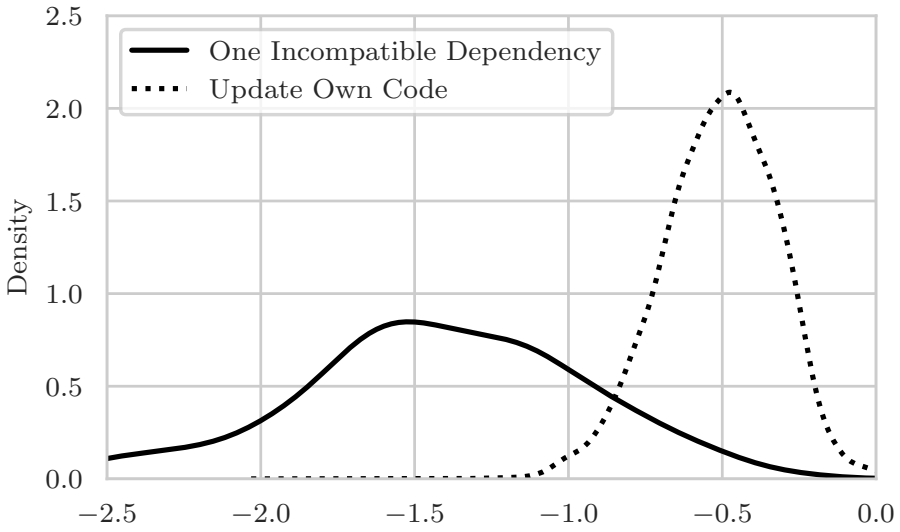


Figure 6: Variable Cost Due to One Incompatible Dependency Versus One's Own Code (convert α^{μ}, α^{s} to the same scale)

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 a cascade effect are captured through $ds_{i,t}$ in this downloads process.

Table 5: Parameter Estimates of Adoption Model (θ_S)

Cost	c_0	2.462***
Parameters		(0.317)
	α^{μ}	0.28***
		(0.021)
	α^{s}	0.113**
		(0.061)
Discount Factor	β	0.953***
		(0.007)
Log Likelihood		-6896.64
Number of Packages		3397
Number of Observations		18917

Table 5 summarizes the estimation results of the structural 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 $\alpha^{\mu} \cdot \mu_{i,t}$; and 3. cost to update one's own code $\alpha^{s} \cdot s_{i,t}$. Both $\mu_{i,t}$ and $s_{i,t}$ are measured in the unit of logarithm 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 logarithm of package size for a dependency is 5.05, and the average cost of dealing with one incompatible dependency is $\alpha^{\mu} \times 5.05 = 1.41$. In comparison, the average size for a package is 4.52, and the average cost of updating one's code is $\alpha^{s} \times 4.52 = 0.51$, which is approximately one-third of the cost of dealing with one incompatible dependency. The relative high cost of dealing with one incompatible dependency is not too surprising. Package developers are more familiar with 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 challenging. At the same time, it is not always easy to find a good alternative package that provides exactly the same functionality as the existing dependency.[39]

The estimate of the six-month discount factor is 0.953, which is equivalent to 0.908 at the annual level or 0.992 at the monthly level. This estimate is not substantially different from the estimates of discount factors in other industries (e.g., 0.988 in De Groote and Verboven (2019)) and very close to the standard monthly discount-factor assumption of 0.99.

7.2 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.

We run simulations of adoption decisions. Starting from the first period, we simulate Python 3 adoption decisions for all packages over time. We run the same simulation 100 times and plot the average simulated adoption rate against the actual rate in Figure 7. The simulated adoption curve fits well in the earlier periods but under-predict the adoption rate by approximately 12% by the end of the sample period.

7.3 Extension Results

Relaxing Assumption 2. The model estimates from relaxing Assumption 2 can be found in the column (2) of Table 6. The estimates do not differ significantly from those in the baseline model. This result confirms our prior belief that though packages should consider the impact of its own decision on its downstream packages in theory, it's not a major concern in practice, simply because there is no systematic way for

[39] In theory, the cost to deal with an incompatible dependency depends on the availability of alternative packages. Unfortunately, we are unable to account for this factor in the cost function due to the lack of a systematic method to identify competing packages.

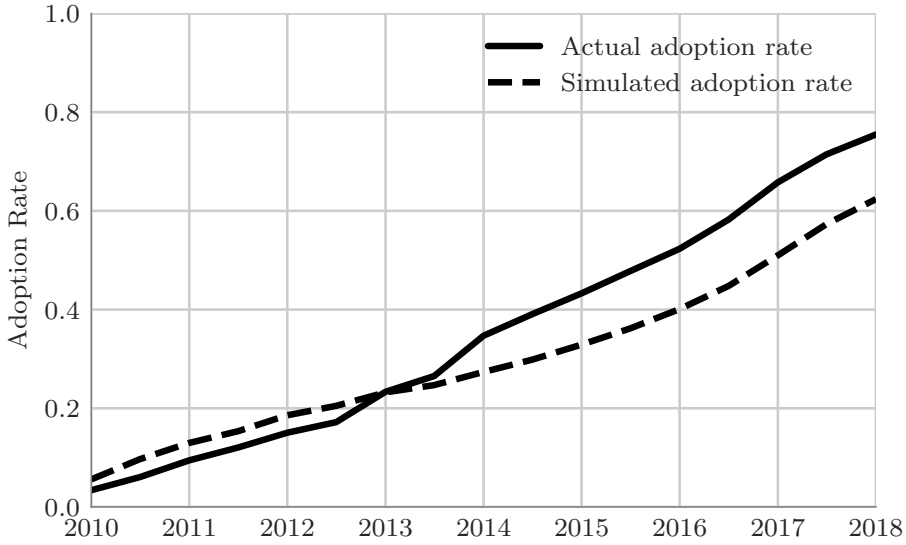


Figure 7: Actual vs. Simulated Adoption Rates

a package to know who its downstream packages are and how much of its downloads come from a downstream package.

Heterogeneity in the discount factor. The rich specification of the discount factor in equation 23 allows us to examine heterogeneity in future costs and benefits from adoption across package developers. The estimates can be found in column (3) of Table 6. Figure 8 plots the histogram of discount factor estimates for all packages. The two-cluster estimates indicate two types of packages, that is, well-maintained packages (most of the packages in our data) that seriously consider the intertemporal tradeoffs and causal or hobby projects where incentives are not captured by our model.

Static model. In comparison with existing literature of social networks, one main feature of our model is the forward-looking behavior. The tradeoff between the current versus future benefits and costs is key to the model. To show that the dynamics are not trivial in our setting, we re-estimate the model by shutting down the dynamics, that is, impose $\beta = 0$. The estimation results are shown in column (4) of Table 6. Figure 9 compares the actual adoption rate to simulated adoption rate from the static and dynamic models. Overall, the static model performs worse in predicting adoption rate than the dynamic model. The static model over-predicts adoption by an additional 10% in the earlier periods and under-predicts by an additional 5% in later periods.

8 Counterfactuals

Katz and Shapiro (1985) predict that the success of a new technology and the speed

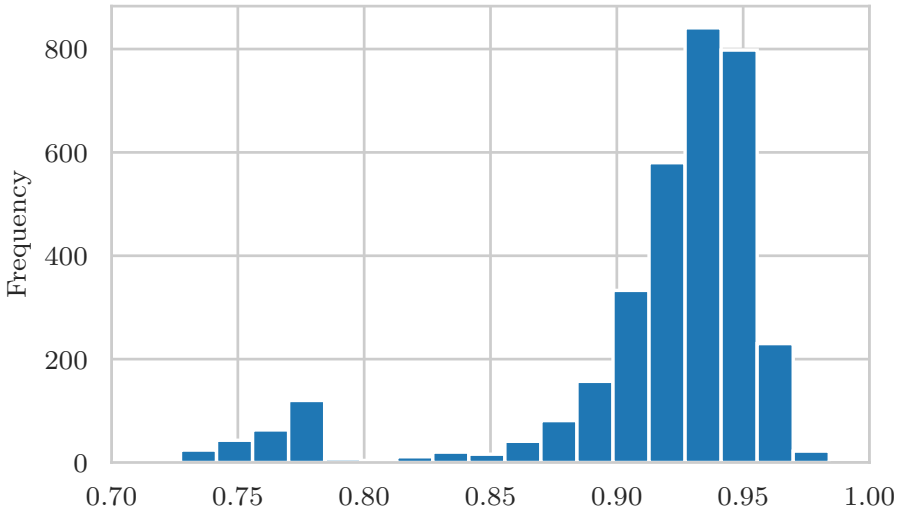


Figure 8: Distribution of Discount Factor $\hat{\beta}_i$

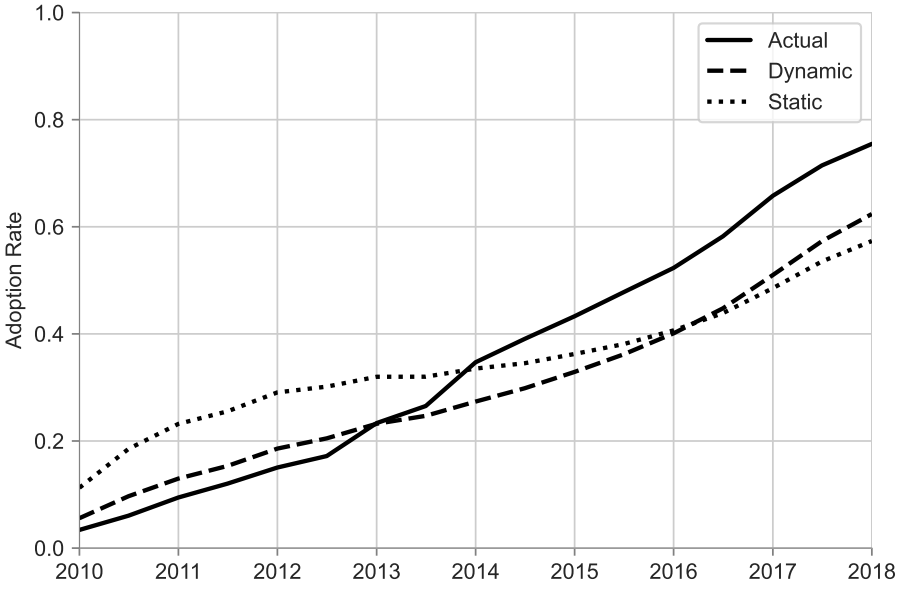


Figure 9: Static vs. Dynamic Model Prediction

Table 6: Comparison of Adoption Parameter Estimates (θ_S)

		(1) Baseline	(2) Ext. Relax Ass.2	(3) Ext. β_i	(4) Ext. Static
Cost	c_0	2.462***	2.475***	2.226***	1.753***
Parameters		(0.317)	(0.32)	(0.311)	(0.06)
	α^μ	0.28***	0.279***	0.259***	0.203***
		(0.021)	(0.021)	(0.023)	(0.015)
	α^s	0.113**	0.121**	0.088**	0.022**
		(0.061)	(0.059)	(0.041)	(0.013)
Discount Factor	β	0.953***	0.954***		
		(0.007)	(0.009)		
	λ_0			0.323***	
				(0.135)	
	λ_1			0.01	
				(0.012)	
	λ_2			-0.154	
				(0.346)	
	λ_3			0.018	
				(0.098)	
	λ_4			0.245***	
				(0.075)	
Log Likelihood		-6896.64	-6889.94	-6816.51	-6997.42
Number of Packages		3397	3397	3397	3397
Number of Observations		18917	18917	18917	18917

of technology adoption highly depend 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). This is a nonprofit organization that oversees various issues in the Python community, including the transition from Python 2 to 3. Given a limited amount of resources, it is critical to understand how to efficiently allocate resources to avoid excess adoption inertia and promote a faster rate of adoption of Python 3.[40]

In this section, we examine the effectiveness of two counterfactual policies to promote faster Python 3 adoption: a lower fixed adoption cost and a scenario without dependency-incompatibility issues. These policies help us to better understand how much Python 3 adoption is affected by the various components of the adoption cost. We first conduct these exercises for both the entire Python community. Then we explore heterogeneous effects across different sub-communities within Python, the results of

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

which can help seeking an "optimal" policy of cost subsidies to various sub-communities within Python.

These counterfactual exercises explore the role of different adoption cost components in Python 3 adoption rate. They provide some guidelines of "optimal" promotion policy to PSF. However, we are unable to measure the exact monetary values of these policies due to data limitations. Ideally, the adoption cost can be measured by tallying the labor input related to the adoption decision, such as the time required to learn the new syntax and update the code to maintain compatibility. Without labor input data, an alternative method involves measuring changes in the actual code from Python 2 to Python 3 and assume a labor cost to produce those code. Still, the estimates would highly depend on certain assumptions.[41] For these reasons, we abstract away from measuring the cost of lowering adoption cost by PSF and focus instead on the effect of different components on the dynamics of Python 3 adoption.

8.1 Lower Adoption Costs

As explained in Section 4.3, the fixed adoption cost comes from multiple sources, including learning the differences in the language syntax and maintenance cost of future releases of a package. The reduction of c_0 can be achieved in various ways with the support of PSF. For example, a better automatic conversion tool from Python 2 to 3 and a higher level of compatibility through scheduled deprecation.[42] The other counterfactual scenario is the case without any dependency-incompatibility issues.[43] That is to say, a package wanting to adopt Python 3 still has to learn the new syntax and update its own code, but it is free to use a dependency that supports Python 2 only.[44]

Figure 11 contrasts the simulated adoption rates from the two counterfactual scenarios. In the scenario of halving the fixed portion of the adoption cost (the dash-dotted line), the adoption rate increased by roughly 10% by the end of 2018. In other words, the cost reduction can help accelerate by one year from 2018 to 2017. The gap between the simulated and counterfactual adoption rates is smaller at the beginning, and it grows and stabilizes by the end of the sample period. The counterfactual result without incompatible dependency issues shows a different pattern (the dotted line). It starts off very close to model simulation but the gap grows larger over time. By the

[41] In the tech industry, the idea of payment based on lines of code is notoriously criticized. In 1990, Microsoft broke off with IBM due to the latter's use of lines of code to measure programmer productivity.

[42] We do not study the optimal compatibility decision made by PSF in this paper. The official reason for the incompatibility between Python 2 and 3 is the high development cost. In this paper, we focus on measuring the benefits of a lower adoption cost.

[43] We thank an anonymous referee for suggesting this counterfactual scenario.

[44] This has been possible in other programming languages such as Fortran where dependencies can be written using an incompatible standard. We assume the same in the case of Python, although the implementation of this idea might be technically difficult.

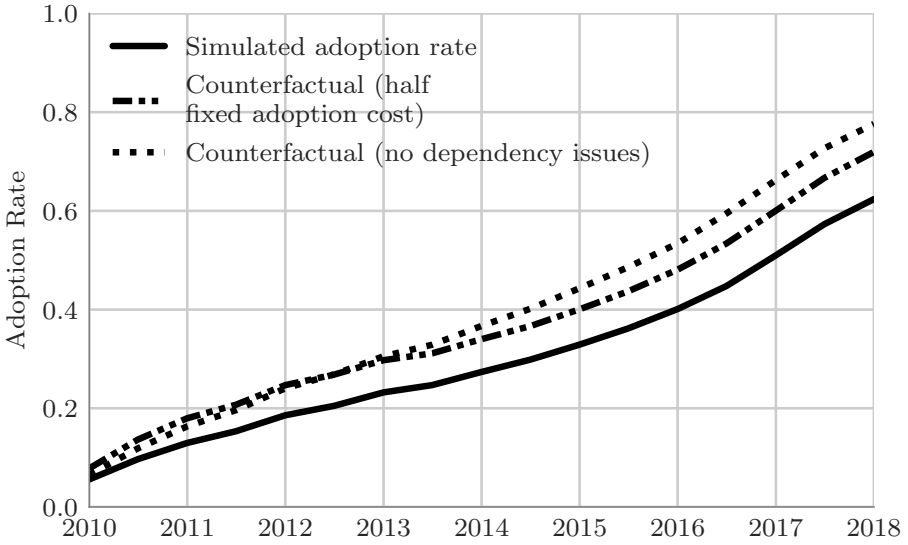


Figure 10: Simulated Adoption Rate with Lower Adoption Cost

end of 2018, a counterfactual scenario shows an increase of 18% in adoption rate, or accelerate the adoption by approximately 1.5 years.

The adoption rates comparison between two counterfactuals is very interesting because it indicates how the roles of the two cost components change over time. The fixed adoption cost component is static in that all packages adopting Python 3 have to pay that cost, regardless of the time or network. The incompatible dependency is a more dynamic issue in the sense that the dependency network evolves over time. With more Python packages becoming available and existing packages getting more functionality, packages are more interconnected over time, and the network starts to play a larger role in the adoption decisions. To examine the differences between the two adoption curves, we first calculate the gap between the two curves, and then calculate the changes of that gap over time. Figure 11 plots the differences of adoption speed between the two counterfactual scenarios. In other words, it shows how much faster the second counterfactual predicts compared to the first one in each period. Figure 11 shows a non-monotonic pattern. In early time periods, the two cost reductions have similar effects to adoption rates. Over time, as packages get more interconnected, the incompatible-dependency issue becomes a bigger obstacle to stall the adoption process. In the first half of 2014, a counterfactual without dependency issues predicts 1% additional adoption rate compared to the case with half fixed adoption cost. Towards the end of the sample periods, as most fundamental packages have adopted Python 3, the incompatibility dependency issue becomes less pronounced and the differences between the two counterfactuals become smaller.

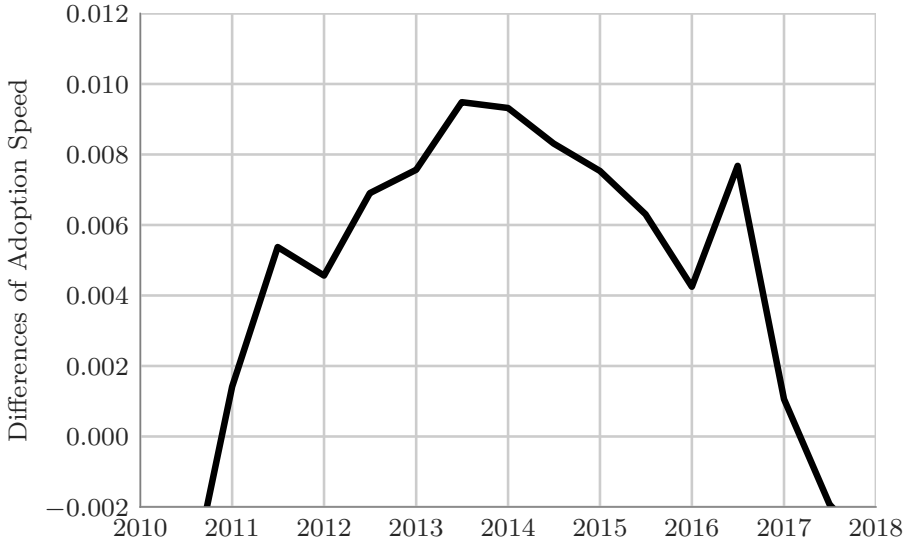


Figure 11: Differences of Adoption Speed Between Two Counterfactual Scenarios

8.2 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 forms 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 a 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 communities.[45]

8.2.1 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 domain can customize it for their own use (for example, 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

[45] Another example of such subsidy can be found in the field of artificial intelligence (AI). AI adoption can be beneficial in many fields, and government agencies have been allocate funding resources to promote AI adoption. See "Canada-UK Artificial Intelligence Initiative" for a recent example.

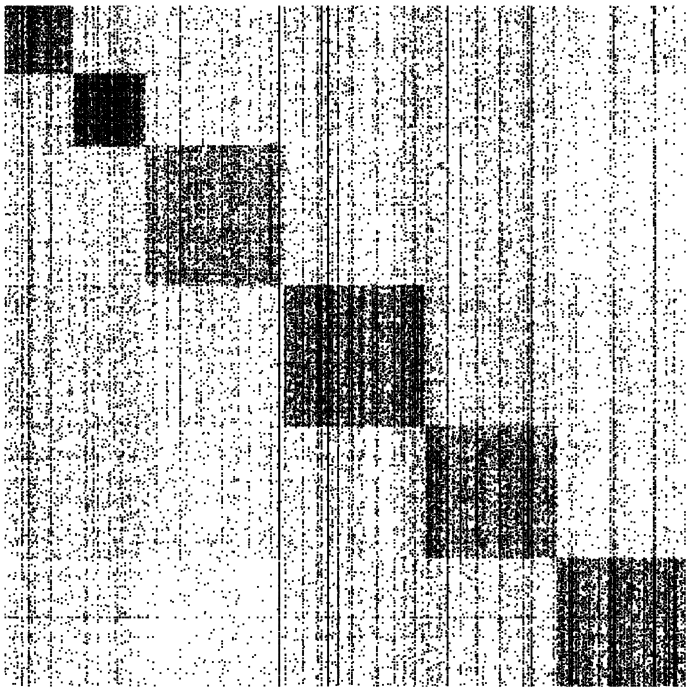


Figure 12: Python Community through Dependency Network

re-adjust the adjacency matrix, which clusters packages into six major communities. Figure 12 plots the updated adjacency matrix. Each dot represents a dependency between two packages, and 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.

Table 7: 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 describes the functionalities and characteristics of packages for each of the six communities in our study. They vary in size as well as network structure. For example, a package in the web development community has an average of 2.573 depen-

dencies and 2.215 downstream packages, whereas the average number of dependencies doubles the number of downstream packages in software development.

8.2.2 Policy Evaluation

We examine the effectiveness of community-level targeted subsidies on the adoption rates through both direct effects within that community and indirect effects on other communities, because communities are all interlinked in different ways. For each community, we adopt the two cost subsidy policies discussed at the beginning of Section 8: 1. reduce the fixed adoption cost by half; 2. no dependency-incompatibility issues. We run the simulation of such policies for each of the seven communities 100 times each. Then we compare the differences between community-level adoption rates with and without the subsidy.

	1	2	3	4	5	6
1	**9.04%***	0.44%	-0.23%	0.20%	0.25%	**1.88%†**
2	0.70%	**9.80%***	-0.39%	**0.83%†**	0.37%	0.97%
3	0.44%	0.87%	**7.52%***	0.04%	0.57%	0.45%
4	0.01%	0.08%	**-1.67%†**	**7.73%***	-0.39%	0.35%
5	1.01%	0.79%	-0.23%	0.42%	**7.97%***	0.86%
6	0.14%	0.51%	-0.64%	-0.13%	0.77%	**8.83%***

(a) Half Fixed Adoption Cost

	1	2	3	4	5	6
1	**18.31%***	-0.23%	**-1.54%†**	0.23%	-0.24%	-0.05%
2	0.34%	**22.69%***	0.13%	0.57%	0.40%	0.98%
3	**1.69%***	**1.80%***	**16.90%***	0.26%	**1.79%***	**1.83%†**
4	0.57%	0.36%	-0.75%	**12.50%***	0.53%	**1.76%†**
5	-0.84%	-0.62%	-1.37%	0.06%	**14.56%***	**1.91%†**
6	-0.06%	0.53%	-0.07%	0.06%	0.36%	**20.70%***

(b) No Incompatible-Dependency Issues

Table 8: Effectiveness of Community-Level Subsidy (Year 8)

Notes: significance level: * 5% † 10%
Each row represents the targeted community that receives a subsidy equal to half 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.

The responses of community-level adoption rates to the two subsidies are reported in Table 8. Each row represents a targeted community that receives a cost subsidy. Each column shows the changes of community-level adoption rates. For example, in the case of the first policy in Table 8.a, the subsidy received by community 1 has

caused 9.04% higher adoption in community 1 and 0.70% higher in community 2 after eight years. The diagonal elements represent the within-community effects and the off-diagonal elements are the across-community effects of the subsidy. Based on the 100 simulations, the statistical significance levels are also reported. A significance of 5% means that more than 95 out of the 100 simulation results show that the policy changes adoption rates.

Overall, the results show that cost subsidy on a targeted community accelerates adoption in that community and has heterogeneous effects on other communities. There are several additional findings that require more discussion. First, the second cost subsidy policy seems to have a much greater impact on the adoption rate than the first one. This is consistent with what we saw in Figure 11 that except for earlier time periods, the incompatible-dependency issue is more pronounced than at least half of the fixed adoption cost. However, the greater impact is found only for within- not across-communities. Second, the same cost reduction policy has heterogeneous effects for adoption rates within the targeted community. Eight years after the subsidy, the within-community effects range from 7.52% to 9.80Third, 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 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 positive, indicating that the former effect dominates the later for most of the communities.

One natural subsequent question is what is the "optimal" policy? Suppose PSF wants to maximize the overall Python 3 adoption, but it has only limited resources to subsidize costs. Which community should then receive it?

The solution to this question needs to account for both the direct effect of subsidy within that community and the indirect effect on other communities. Moreover, the temporal dimension also matters. Table 9 summarizes the effectiveness of community-level subsidy to the targeted community and the overall Python community over time. Each column represents the targeted 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 5.61% and the overall rate by 0.87% after one year.

Table 9 can be viewed as a tabular version of Figure 11 for targeted community-level cost subsidies. The within-community effects shown in Table 9 is consistent to what we found in Figure 11 that the effect of the second cost subsidy is smaller in the early years but becomes more pronounced in later time as packages become more interlinked. The finding indicates the choice of the "optimal" policy depends on the temporal dimension. Moreover, the temporal dimension is also important for the decision of targeted communities. For example, for the first cost subsidy, community

Table 9: Effectiveness of Community-Level Subsidy

Counterfactual	Half Fixed Adoption Cost						No Incompatible-Dependency Issues					
Target Community	1	2	3	4	5	6	1	2	3	4	5	6
Year 1												
ΔAR_m	5.61%	4.55%	4.60%	6.08%	5.12%	5.20%	4.00%	3.26%	3.97%	4.59%	3.15%	4.36%
$\Delta OverallAR$	0.87%	0.86%	0.89%	1.05%	0.85%	0.87%	0.74%	0.68%	0.87%	0.84%	0.60%	0.44%
Year 2												
ΔAR_m	5.46%	6.09%	5.18%	6.90%	6.53%	7.10%	5.69%	6.54%	6.83%	6.73%	4.54%	6.70%
$\Delta OverallAR$	0.87%	0.87%	1.28%	0.95%	0.95%	0.74%	0.90%	0.99%	1.64%	1.08%	0.84%	0.60%
Year 3												
ΔAR_m	6.46%	6.25%	5.41%	6.70%	6.53%	7.30%	7.18%	10.15%	9.85%	7.99%	7.12%	8.39%
$\Delta OverallAR$	0.92%	0.73%	1.40%	0.85%	1.02%	0.69%	0.94%	1.15%	2.32%	1.10%	1.06%	0.56%
Year 5												
ΔAR_m	7.28%	7.09%	6.84%	7.01%	7.37%	6.51%	13.69%	16.53%	14.85%	10.54%	11.78%	11.23%
$\Delta OverallAR$	0.77%	0.76%	1.65%	0.79%	1.23%	0.72%	1.42%	2.02%	3.38%	1.39%	1.81%	1.12%
Year 8												
ΔAR_m	9.04%	9.80%	7.52%	7.73%	7.97%	8.83%	18.31%	22.69%	16.90%	12.50%	14.56%	20.70%
$\Delta OverallAR$	1.26%	1.47%	1.77%	0.66%	1.35%	1.22%	1.67%	3.16%	4.34%	1.79%	1.67%	2.80%

Notes: This table summarizes the effectiveness of community-level adoption subsidy on the targeted community and the overall adoption over time. Each column represent a different targeted community. ΔAR_m means the simulated changes in adoption rate in the targeted community; $\Delta OverallAR$ means the simulated changes in adoption rate in the whole Python community.

4 seems to be a better target than community 3 in the short term (1.05% vs. 0.89% in the first year), but the result is reversed in the long term (0.66% vs. 1.77% in the eighth year).

Certain communities have strong reactions to the subsidy, but adoption in other communities might stall due to the negative indirect effects. The second cost subsidy targeting community 1 can raise an additional 18.31% adoption rate after 8 years, but it has a small impact of 1.67% for the overall adoption, whereas a subsidy to community 3 can achieve a much larger impact of 4.34% despite a smaller within-community effect of 16.90%.

To further explore the heterogeneous effects on the adoption rates both within and across-community, we regress the effect on the adoption rates on several network and package characteristics. In particular, we want to explore the relationship with network density both within and across communities. Within-community density $Density_m$ follows a standard definition and it is calculated as the number of existing dependencies divided by the total possible dependencies community m could have. Across-community density $Density_{m',m}$ differs from the standard density definition because the dependency network is a directed network. Here we denote community m' as the target community and we'd like to explore the effect on community m. In this case, we are most interested in cases where packages in community m' are dependencies of those in m. We count those cases as the actual number of connections, and we define the total possible connections as the total possible cases where packages in m are downstream packages. We also control for other community-level package

	Half Fixed Adoption Cost			No Incompatible-Dependency Issues		
	(1) $\Delta AR_{m,t}$	(2) $\Delta AR_{m,t}$	(3) $\Delta AR_{m,t}$	(4) $\Delta AR_{m,t}$	(5) $\Delta AR_{m,t}$	(6) $\Delta AR_{m,t}$
$Density_m$	0.359***			0.662***		
	(0.12)			(0.23)		
$Density_{m',m}$		0.970***	2.106***		1.417***	3.152***
		(0.22)	(0.28)		(0.42)	(0.54)
N_m	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
X_m	-0.042***	-0.031***	-0.034***	-0.076***	-0.055***	-0.059***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
S_m	-0.062***	-0.044***	-0.042***	-0.114***	-0.082***	-0.079***
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
$N_{m'}$		-0.000			-0.000	
		(0.00)			(0.00)	
$X_{m'}$		-0.004**			-0.006	
		(0.00)			(0.00)	
$S_{m'}$		0.001			0.001	
		(0.00)			(0.01)	
$Year_t$	0.001	0.001	0.001	0.005	0.005**	0.005**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Year_t^2$	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.893***	0.724***	0.684***	1.598***	1.267***	1.209***
	(0.12)	(0.06)	(0.04)	(0.23)	(0.12)	(0.07)
Target Community	m	m'	m'	m	m'	m'
Model	OLS	OLS	FE	OLS	OLS	FE
N	119	714	714	119	714	714
R^2	0.429	0.402	0.431	0.373	0.339	0.357

Table 10: Effectiveness of Counterfactual Policy and Community Characteristics

characteristics such as community size (N_m), average logged downloads (X_m), average package size (S_m), as well as time trend. Table 10 summarizes the regression results for the two counterfactual cost subsidy policies. The first column in each section explores the within-community effects and the second and third columns report the across-community effects. The dependent variable $\Delta AR_{m,t}$ is calculated as the differences of simulated adoption rates in community m with and without that particular cost subsidy. The first two columns in each section are pooled-OLS regression and the third one uses the target community m' as fixed effects. The within-community estimates

(columns 1 and 4) shows that more densely-connected communities benefit more from cost subsidies. For communities with a dense network, packages in that community are more heavily affected by others and the community can fall into a state with little adoption. The across-community estimates (columns 2, 3, 5, 6) indicate a community m benefits more from cost subsidies targeting another community m' with more of its dependencies. When many packages in m use packages in m' as dependencies, promotion in m' obviously has the largest effect on m', but it also has a relatively larger effect on m.

9 Conclusion

Technological changes have been fundamental to 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 dependency network. We build a structural model of technology adoption to capture the dynamic compatibility decisions of packages that are interlinked through a rich dependency network. Our dynamic model allows each agent to anticipate the future actions of others.

To estimate this adoption model with a network in a feasible fashion, we take advantage of the dependency relationship and propose a novel layered estimation approach, which allows us to conveniently calculate the necessary elements as inputs for those in lower layers. This layered estimation approach significantly reduced our computational burden. 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 promotion policy to accelerate adoption. Simulation results show that when providing subsidies to a certain community of the population, the optimal promotion 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 policymakers should focus not only on the direct effect on the recipients of subsidies, but also on the indirect effect on the whole industry to determine the optimal promotion 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 come 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. That being said, our approach might be too restrictive for networks where prices play a major role. In that sense, our research raises more questions than it can answer. The answers to these more general questions require not only high-quality data for one or multiple industries but also the corresponding development of econometric modeling and estimation methods. We hope that, as one of the first papers to link dynamic models and dependency networks, our work can contribute to further development in this direction.

References

Abbring, Jaap H, and Oystein Daljord. 2019. "Identifying the Discount Factor in Dynamic Discrete Choice Models." *Becker Friedman Institute for Research in Economics Working Paper*.

Aguirregabiria, Victor, and Pedro Mira. 2010. "Dynamic Discrete Choice Structural Models: A Survey." *Journal of Econometrics*, 156(1): 38–67.

Atkin, D, A Chaudhry, Shamyla Chaudry, Amit K Khandelwal, and Eric Verhoogen. 2017. "Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan." *The Quarterly Journal of Economics*, 132(3): 1101–1164.

Bajari, Patrick, C Lanier Benkard, and Jonathan Levin. 2007. "Estimating dynamic models of imperfect competition." *Econometrica*, 75(5): 1331–1370.

Bjorkegren, Daniel. 2018. "The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda." *The Review of Economic Studies*, 37: 1033–1060.

Blondel, Vincent D, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. 2008. "Fast Unfolding of Communities in Large Networks." *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10): P10008–10012.

Cabral, Luis. 2011. "Dynamic price competition with network effects." *The Review of Economic Studies*, 78(1): 83–111.

De Groote, Olivier, and Frank Verboven. 2019. "Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems." *American Economic Review*, 109(6): 2137–2172.

DeLong, J Bradford. 2002. "Productivity Growth in the 2000s." *NBER Macroeconomics Annual*, 17: 113–158.

Dube, Jean-Pierre H, Gunter J Hitsch, and Pradeep K Chintagunta. 2010. "Tipping and concentration in markets with indirect network effects." *Marketing Science*, 29(2): 216–249.

Farrell, Joseph, and Garth Saloner. 1985. "Standardization, Compatibility, and Innovation." *The RAND Journal of Economics*, 16(1): 70–83.

Fershtman, Chaim, and Neil Gandal. 2008. "Microstructure of Collaboration: The Network of Open Source Software." *SSRN Electronic Journal*, 1–40.

Fershtman, Chaim, and Neil Gandal. 2011. "Direct and Indirect Knowledge Spillovers: The "Social Network" Of Open-source Projects." *The RAND Journal of Economics*, 42(1): 70–91.

Geroski, P A. 2000. "Models of Technology Diffusion." *Research Policy*, 29(4-5): 603–625.

Gowrisankaran, Gautam, and Joanna Stavins. 2004. "Network Externalities and Technology Adoption: Lessons from Electronic Payments." *The RAND Journal of Economics*, 35(2): 260–276.

Gowrisankaran, Gautam, and Marc Rysman. 2012. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy*, 120(6): 1173–1219.

Grewal, Rajdeep, Gary L Lilien, and Girish Mallapragada. 2006. "Location, Location, Location: How Network Embeddedness Affects Project Success in Open Source Systems." *Management Science*, 52(7): 1043–1056.

Hall, Bronwyn, and Beethika Khan. 2003. "Adoption of New Technology." *New Economy Handbook*, 1–21.

Hall, Bronwyn H. 2009. *Innovation and Diffusion.* Oxford University Press.

Hendel, Igal, and Aviv Nevo. 2006. "Measuring the Implications of Sales and Consumer Inventory Behavior." *Econometrica*, 74(6): 1637–1673.

Hollenbeck, Brett. 2017. "The economic advantages of chain organization." *The RAND Journal of Economics*, 48(4): 1103–1135.

Hu, Mandy Mantian, Sha Yang, and Daniel Yi Xu. 2019. "Understanding the social learning effect in contagious switching behavior." *Management Science*, 65(10): 4771–4794.

Katz, Michael L, and Carl Shapiro. 1985. "Network Externalities, Competition, and Compatibility." *American Economic Review*, 75(3): 424–440.

Katz, Michael L, and Carl Shapiro. 1986. "Technology Adoption in the Presence of Network Externalities." *Journal of Political Economy*, 94(4): 822–841.

Keane, Michael P. 1994. "A Computationally Practical Simulation Estimator for Panel Data." *Econometrica*, 62(1): 95–116.

Keane, Michael P, and Kenneth I Wolpin. 1997. "The Career Decisions of Young Men." *Journal of Political Economy*, 105(3): 473–522.

Macher, J, N H Miller, and M Osborne. 2020. "Technology Adoption in the Cement Industry." *The RAND Journal of Economics*.

Magnac, Thierry, and David Thesmar. 2002. "Identifying Dynamic Discrete Decision Processes." *Econometrica*, 70(2): 801–816.

Mansfield, Edwin, Ruben F Mettler, and David Packard. 1980. "Technology and Productivity in the United States The American Economy in Transition." In . 563–616. University of Chicago Press.

Max Wei, Yanhao. 2020. "The similarity network of motion pictures." *Management Science*, 66(4): 1647–1671.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica*, 55(5): 999–1033.

Rust, John, and Christopher Phelan. 1997. "How Social Security and Medicare Affect Retirement Behavior in a World of Incomplete Markets." *Econometrica*, 65(4): 781–751.

Ryan, Stephen P, and Catherine Tucker. 2011. "Heterogeneity and the Dynamics of Technology Adoption." *Quantitative Marketing and Economics*, 10(1): 63–109.

Saloner, Garth, and Andrea Shepard. 1995. "Adoption of Technologies with Network Effects: An Empirical Examination of the Adoption of Automated Teller Machines." *The RAND Journal of Economics*, 26(3): 479–501.

von Krogh, Georg, Stefan Haefliger, Sebastian Spaeth, and Martin W Wallin. 2012. "Carrots and Rainbows: Motivation and Social Practice in Open Source Software Development." *MIS Quarterly*, 36(2): 649–676.

Xu, Lei, Tingting Nian, and Luis MB Cabral. 2020. "What Makes Geeks Tick? A Study of Stack Overflow Careers." *Management Science*, 66(2): 503–1004.

10 Appendix

10.1 Examples of Python 3 New/Incompatible Features

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

One of the most fundamental features that makes 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 can basically only deal with English characters, punctuation, and digits that can be found on a standard English keyboard. Non-English characters have to be dealt with 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 the division of integers. In Python 2, like all other major programming languages, the division sign "/" means floor division; for example, $5/2 = 2$. 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.

10.2 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

```
A = [1,2,3]
B = [1,1,0]
result = 0
for i in range(3):
    result = result + A[i] * B[i]
```

B. With Package NumPy

```
import numpy
A = numpy.array([[1,2,3]])
B = numpy.array([1,1,0])
A @ B
```

One can multiply two matrices $A = \left(\begin{smallmatrix}1\\2\\3\end{smallmatrix}\right)$ and $B = \begin{pmatrix}1 & 1 & 0\end{pmatrix}$ with dimensions 3x1 and 1x3 respectively using Python by creating two lists, looping through the two lists, and then summing up the multiplied value; that is, $1\times1+2\times1+3\times0 = 3$. Alternatively, 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 prone to error, and more computationally efficient, especially with large and multi-dimensional matrices.

10.3 Variations in the Raw Data

Table 11: Logistic Regression Model

	(1)
	$d_{i,t}$
$x_{i,t-1}$	0.172***
	(0.02)
$\mu_{j,t}$	-0.209***
	(0.02)
$s_{i,t}$	-0.056***
	(0.01)
Constant	-3.135***
	(0.14)
N	18917
LLH	-6958

One way to show data variations essential for identification parameters is through a simple logistic regression. Table 11 reports results from such a logistic regression without the complexity of the structural model of adoption. All the estimates are significant, indicating that there are nice raw data variations that are helpful for structural model identification.

10.4 Empirical Evidence for Assumption 1

The main reason for making the sequential-move assumption is that dependency packages often pre-announce their plans for future releases. The simplest way to verify this is to calculate the frequency of pre-announcement by upstream/dependency vs. downstream packages. Such information is often easy to find under the "roadmap" section on each package's website. However, this piece of information is not systematically recorded in a central depository. At the same time, for a limited number of packages, the roadmap information is provided under the Description section on PyPI. Therefore, instead of scraping all the packages' websites, we simply count the occurrences of "roadmap" found in the Description section for all the upstream-downstream

package pairs. We don't think this crude measure would differ much from a more accurate data collection from scraping all the websites.

Table 12: Number of Occurrences with Roadmap Information

Both have roadmap	17
Only upstream/dependency package has roadmap	830
Only downstream package has roadmap	75
Neither has roadmap	5,285

Table 12 lists the number of occurrences for each of the four scenarios. In most cases (5,285 occurrences), neither the upstream nor the downstream packages has roadmap information, probably due to the crudeness of this measure (i.e., roadmap information is provided on their own website instead of on PyPI). Conditional on having some roadmap information, it is mostly likely the case that only the dependency package has the information (830 occurrences), which supports the sequential-move assumption based on the dependency relationships.