

# The Death of a Technical Skill

John J. Horton                      Prasanna Tambe\*  
MIT Sloan and NBER              Wharton, U. Penn

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## Abstract

In 2010, Steve Jobs announced that Apple would no longer support Adobe Flash—a popular set of tools for creating Internet applications. After the announcement, the use of Flash declined precipitously. We show there was no reduction in Flash hourly wages because of a rapid supply response: Flash specialists, especially those who were younger, were less specialized, or had good “fall back” skills quickly transitioned away from Flash; new market entrants also avoided Flash, leaving the effective supply per Flash job opening unchanged. As such, there was no factor market reason for firms to stay with Flash longer.

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\*For the latest version, see <https://www.john-joseph-horton.com/papers/schumpeter.pdf>. We acknowledge valuable feedback from seminar participants at the NBER IT and Digitization Summer Institute, the INFORMS Conference on Information Systems and Technology, Cornell University, Arizona State University, the Rotterdam School of Management, the University of Texas-Austin, the University of Maryland, and the University of Utah. Thanks to James Bessen, Apostolos Filippas, Richard Zeckhauser, Chis Stanton, David Autor, Rob Seamans, Jacques Crémer, Adam Ozimek, Sebastian Steffen, Andrey Fradkin, Emma van Ingwen, Joe Golden, and Daniel Rock for helpful comments and suggestions. Prasanna Tambe is grateful for financial support from the Alfred P. Sloan foundation. John Horton is grateful for financial support from the Upjohn Institute. Thanks to Jeff Bigham and Elliot Geno for insight into the labor market for Flash skills. For a version of this paper with all code included as an appendix, see [https://www.john-joseph-horton.com/papers/schumpeter\\_with\\_code.pdf](https://www.john-joseph-horton.com/papers/schumpeter_with_code.pdf).

# 1 Introduction

When the demand for a skill falls—or will foreseeably fall—workers with that skill must make a choice. If they choose to “exit,” they can leave the workforce, learn a new skill, or work with another skill they already possess. If they choose to stay, they face the lower wages or worsened job-finding probability this choice entails. Workers who are entering the labor market—but disposed to working with the declining skill—have to make an analogous decision. The choices made by both incumbent and entrant workers presumably depend on factors such as their career horizon, ability level, and current human capital. They also must consider the anticipated course of the decline in demand and the costs of switching to a new skill. Workers might also need to consider the collective choices of all other similarly situated workers. In broad terms, this characterization of the human capital allocation problem is not novel (Ben-Porath, 1967; Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1996), but there is relatively little fine-grained evidence on how individual workers adjust to a skill-specific demand shock. And yet it is the fine-grained details of adjustment that have implications for worker welfare, the diffusion of technology, and the rate of innovation (Acemoglu, 1998).

In this paper, we explore how the labor market for a technical skill responded to a negative shock in the demand for the technology. The skill that we study is Adobe Flash—a once-popular collection of software tools used for creating multimedia games, advertisements and applications delivered over the Internet. The decline in demand for Flash skills is widely attributed not to the emergence of a superior technology, but rather to a business decision made by Apple. On April 29th, 2010, Steve Jobs—the CEO of Apple at the time—published an open letter entitled “Thoughts on Flash” (TOF), which announced that Apple would no longer support Flash on iOS devices such as the iPhone, iPod, and iPad.<sup>1</sup> The announcement was widely covered by the news media. Despite Jobs’ claims that the decision was made for technical reasons, this was viewed by many as a pretext—the “real” reason for this withdrawal of support was a desire for greater control over the experience on Apple devices, particularly the iPhone.<sup>2</sup> Even if Jobs’ arguments had techni-

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<sup>1</sup><http://www.apple.com/hotnews/thoughts-on-flash/>.

<sup>2</sup>The contemporaneous discussion of the announcement on Hacker News, a discussion site run by Y Combinator and known for insider takes on IT and the startup/tech industry—is illustrative, as it contains many arguments that Apple’s choice was self-interested and made on flimsy technical arguments—see <https://news.ycombinator>.

cal merit, it was clearly self-serving for Jobs to make them at that particular moment in time.

Jobs’ motivations and reasons notwithstanding, this announcement was viewed by the developer community as an inflection point in the market for Flash development, and our data suggest it was an effective—albeit slow-acting—poison. The decline in Flash can be observed in a variety of data sources. Perhaps the best contemporary indicators of software developer interest in a given technology are the questions being asked on Stack Overflow, an enormously popular programming Q&A site. The left facet of Figure 1 shows the volume of questions per month for Flash and for comparison, a basket of popular IT skills, all normalized to 1 in the TOF month.<sup>3</sup> The y-axis is on a log scale. We can see from this comparison that the numbers of questions about Flash and our chosen basket of skills are growing more or less in lockstep pre-TOF, reflecting growth in the Q&A platform and the wider IT industry, but that after TOF, Flash shows a clear absolute decline. There is some delay in this drop, likely reflecting the diffusion of the news of Apple’s plans as well as the completion of already-planned projects.

To study how the decline in Flash affected workers specializing in Flash, we use data from a large online labor market (Horton, 2010). The decline in Flash is also readily apparent in the longitudinal data from this market: the right facet of Figure 1 plots the number of job openings posted per month for jobs requiring Flash skills and for those requiring PHP (one of the “basket skills” from the left facet of Figure 1). Both Flash and PHP are normalized to 1 for the TOF-month. For comparison, we truncate the data to the first year of the Stack Overflow data (in 2008), even though the online labor market is considerably older. As we saw with the Stack Overflow data, both Flash and PHP move closely together pre-TOF and then diverge. Following TOF, the number of Flash job openings began to decline relative to PHP, falling by more than 80% between 2010 and 2015.

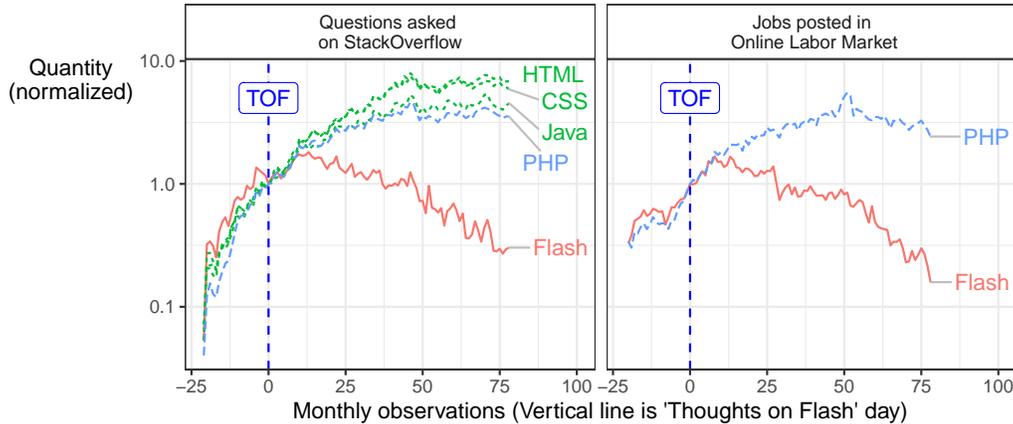
As we will show, despite a large decline in the number of Flash openings posted, very little else about the market for Flash changed. There is no evidence employers were inundated with applications from out-of-work Flash programmers—the number of applicants per opening remained roughly con-

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com/item?id=1304310.

<sup>3</sup>HTML is a markup language for making websites; CSS is a language for styling websites and controlling their appearance; Java is a general purpose programming language, while PHP is another programming language frequently used for server-side scripting.

Figure 1: The decline of Flash on two platforms



*Notes:* The left facet plots number of questions, by technical skill, posted on Stack Overflow between 2008 and 2016. The right facet shows the number of job posts requiring Flash or PHP in an online labor market. All series are normalized to have a value of 1 in the TOF period. The unit of observation is the month.

stant.<sup>4</sup> There was no increase in the likelihood that Flash openings were filled, nor was there a reduction in the wages paid to hired Flash programmers. In short, despite a roughly 80% reduction in posted Flash jobs, we observe a reduction in the quantity of hours-worked, but no reduction in the price.

In contrast, when the level of analysis is the individual Flash-specializing worker, large changes are apparent. We see substantial movement away from Flash, as measured by counts of active Flash workers. As demand for Flash starts to fall, more workers begin exiting the market for Flash than entering it, despite the platform itself growing rapidly. This early movement is evident in the time series of active Flash workers, with a net flow out of Flash even when the number of job postings was roughly flat. We also observe this in hours-worked per active Flash worker, which actually *increases* over time, contrary to the idea of a large pool of out-of-work Flash workers competing for a dwindling pool of jobs.

Market aggregates potentially mask compositional changes in the types of Flash jobs posted or the workers participating. For example, flat wages could mask a real decline if the remaining Flash work is being done by the most

<sup>4</sup>We use the terms “worker” and “employer” for consistency with the economics literature, and not as a comment on the nature of the relationships created on the platform.

experienced Flash workers. To understand the decision-making and outcomes of individual Flash workers, we constructed a panel of workers specializing in Flash prior to TOF, as well as a control group that was also active on the platform pre-TOF, but that specialized in other non-Flash IT skills. Our empirical approach is essentially a difference-in-differences design, using the contemporaneous non-Flash developers as a control group. Rather than use all workers active on the platform as controls, we selected a sample with similar attributes at the time of the TOF. Because of the large number of potential “donor pool” workers on the platform, we obtain excellent balance on pre-TOF covariates, such as average wages, job search intensity, hours-worked, and experience.

Using the matched sample panel, we find no evidence that Flash workers were more likely to exit the online labor market post-TOF, making it unlikely that selection explains our results. As with the market-level time-series evidence, we find no evidence of a reduction in the hourly wage. On the contrary, at the worker level, there is some evidence of an *increase* in the hourly wage for the most experienced Flash workers.

Our panel allows us to explore when incumbent workers began moving away from Flash and which workers began moving. We find evidence that workers specializing in Flash prior to TOF increased their job search intensity—submitting more applications per month. The effects are concentrated among those workers who were more focused on Flash pre-TOF, as measured by the fraction of their hours-worked that were on Flash projects. In addition to increasing application intensity, Flash workers also shifted their job search *focus*, as measured by how similar a job they applied to is to the kinds of jobs the worker had completed in the past. We find strong evidence that they began moving away from their existing skill focus, applying to jobs that were less like jobs they had worked on in the past. This movement away from Flash occurred when the decline in demand was still nascent and Flash openings were still fairly plentiful.

If the hourly wage for Flash work did not fall, why did incumbent Flash workers switch? One possible explanation is that Flash workers were infinitely elastic to changes in the Flash market. At the level of the individual, this would seem improbable for a skill that requires a significant human capital investment. We also show empirically that experience in Flash does not fully transfer to higher productivity in non-Flash skills, and vice versa. Even if many workers are individually inelastic, the supply curve could be *de facto* highly elastic if enough workers decide not to enter and enough workers exit

(to learn new skills) before a collapse in demand. This type of adjustment would be particularly effective if other skill markets are sufficiently large that Flash “refugees” are not likely to depress wages very much (Card, 1990). We formalize this idea in a simple model that shows how wages for a dying skill can stay flat or even increase, depending how incumbents and would-be entrants respond to a demand shock.

There is heterogeneity in the choices made by individual workers and their outcomes. Although there was no decline in wages on average, workers who were older seemed to have experienced wage declines, whereas younger workers experienced modest wage increases. Older workers also experienced declines in hours-worked that younger workers did not. We also observe that younger workers increasingly demanded a premium to work with Flash post-TOF, whereas older workers did not.

In addition to our empirical analysis of platform observational data, we surveyed 186 former Flash developers still active on the platform to understand their interpretation of the Flash controversy, how it affected them, and what types of adjustments they made in response to the changing market. The results of this survey are shown in Appendix A. These survey responses provide evidence consistent with the evidence from the online labor market, while also elucidating qualitatively how workers perceived changes to their market and how they considered their choices.

A key finding of the paper is that when demand fell, forward-looking workers moved to other skills, particularly those with a longer career horizon. This provides an explanation for why there was so little reduction in Flash wages at the market level—the negative demand shock was offset by a supply response. For a skill that requires substantial human capital—and with that human capital mostly acquired through on-the-job training—the future market for a skill strongly affects the value of work done in the present.

This is the first paper of which we are aware that uses longitudinal fine-grained wage, hours, and application data to study how a market adjusts when an information technology become “obsolete.” Although there is a large literature on workers’ responses to adverse shocks (Jacobson et al., 1993; Kletzer, 1998; Couch and Placzek, 2010; Nedelkoska et al., 2015), our setting has several features that are novel when exploring human capital decision-making. Because of the online setting, the shock is “pure” without the other associated equilibrium effects that might occur from more geographically localized shocks (say from a plant closing), or that are confounded with other effects of the business cycle (von Wachter et al., 2009; Davis and von Wachter,

2011; Kahn, 2010). The project-based, relatively short-term nature of the work implies any losses from skill obsolescence are likely not due to firm-specific human capital (Neal, 1995) or even firm-specific rents (Goldschmidt and Schmieder, 2017). Our paper is most conceptually similar to Edin et al. (2019), which looks at how individual outcomes are correlated with broad declines in occupations. They find surprisingly small reductions in earnings—far smaller than found from specific worker displacements—consistent with our results.

A key point of differentiation between our paper and the existing literature on technological change and labor markets is that most of this prior work focuses on longer time scales than our study (Chin et al., 2006; Goldin and Katz, 2007). If technical change takes longer, we might expect different modes of adjustment, such as changes in the productive process with respect to broad types of labor inputs (Bresnahan et al., 2002; Autor et al., 2003; Michaels et al., 2014) or changes happening only at the generational level (Goldin and Katz, 1999). In our setting, the decline of Flash occurred within the career horizon of a large number of workers and so “within-worker” adjustment was necessary. This kind of rapid change is currently of significant interest due to the anticipated effects of emerging technologies—such as AI and sharing economy platforms—on the workforce (Filippas et al., forthcoming; Chen et al., Forthcoming; Hall and Krueger, 2018).

The labor market for technical skills is of particular interest because this market is often characterized as having “shortages” despite the high wages. Deming and Noray (2018) show that the returns to STEM majors/occupations decline considerably over time, due to technological obsolescence. Unlike their setting, the comparisons we make are between different vintages of technical skills. In fact, our setting is an example of a key point Deming and Noray (2018) makes—STEM occupations are characterized by rapid technological change, with workers having to adapt frequently as old human capital becomes less valued. This has implications for entry into STEM, as well as the micro-details of adjustment to these shocks, which is our focus.

Many new technologies have a complementary labor component, and the diffusion of that technology could depend on how quickly complementary skills appear, and how expensive they are relative to those that complement the “old” technology. If hiring workers with a waning skill became dramatically cheaper, we might see more use of the old technology than we otherwise would. Our results imply this concern is unfounded, and that if anything, the labor market response would help accelerate diffusion, as workers also try to

get ahead of where technology is heading.

The rest of the paper is organized as follows. Section 2 discusses the Adobe/Apple Flash controversy and the empirical context of study. Section 3 presents descriptive statistics on the Flash market. Section 4 discusses the economics of market adjustment to a decline in demand. Section 5 presents the outcomes and choices of individual workers. Section 6 explores what “fall back” skills workers pursued. Section 7 concludes.

## 2 Empirical context

Flash applications can be technically complex, typically requiring a mix of programming, graphic design, and other complementary skills. A would-be Flash programmer must learn the underlying programming language, ActionScript, as well as Adobe’s Flash authoring tools and best practices for building and debugging Flash applications. Even for programmers who are experienced in other programming languages, acquiring Flash skills would be a non-trivial investment, requiring months or even years of sustained effort.

To give a sense of the size of the human capital investment in learning Flash, the last published Flash user’s guide is over 527 pages, and the full documentation (made up of HTML files) is nearly 17 *million* words. There are hundreds of books on Flash still listed on Amazon.<sup>5</sup>

### 2.1 Apple’s announcement

On April 29th, 2010, Apple’s CEO Steve Jobs published an open letter, “Thoughts on Flash,” announcing Apple’s decision to no longer support Flash applications on the iPhone, iPad or iPod Touch. Immediately following the release of Jobs’ letter, shares of Adobe fell more than 1%.<sup>6</sup> While

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<sup>5</sup>As of June 22, 2019, there are still over 350 books returned on Amazon.com for the query ‘Adobe Flash’: <https://www.amazon.com/s?k=Adobe+Flash><https://www.amazon.com/s?k=Adobe+Flash>. The user’s guide is here: [https://www.adobe.com/support/documentation/archived\\_content/en/flash/cs3/flash\\_cs3\\_help.pdf](https://www.adobe.com/support/documentation/archived_content/en/flash/cs3/flash_cs3_help.pdf). The documentation word count was obtained by downloading [http://help.adobe.com/en\\_US/FlashPlatform/reference/actionscript/3/PlatformASR\\_Final\\_en-us.zip](http://help.adobe.com/en_US/FlashPlatform/reference/actionscript/3/PlatformASR_Final_en-us.zip) and running: `find . -name *html -type f -print0 | xargs -0 wc | tail -n 1` on the unzipped folder.

<sup>6</sup>Apple’s Jobs slams Adobe’s Flash technology.

Jobs claimed that technical considerations were driving Apple’s announcement, it was widely believed that these arguments were a pretext and that Apple wanted to withdraw support from Flash because it was unwilling to concede so much control over the user interface and device performance to third parties.<sup>7</sup> Tony Bradley, of PC World, wrote:<sup>8</sup>

It boils down to Apple wanting to maintain tight, proprietary control over app development for the iPhone and iPad, and not wanting to share the pie. It also seems suspicious given Apple’s foray into mobile advertising with the iAd platform competing directly with the fairly ubiquitous Flash-based ads.

In the years following Jobs’ letter, the popularity of Flash waned considerably, though the effect was not immediate nor universally anticipated: on August 26th, 2010 the Wall Street Journal touted rising demand for Flash workers—a “trend” that seems to have had no empirical basis.<sup>9</sup> It also appears that Apple’s decision might have catalyzed other changes in the industry that hastened the demise of Flash. For example, in late 2011, it was announced that Flash would no longer be natively supported on the Android operating system, starting with the “Jellybean” release.<sup>10</sup> Although still used for some applications today, the decline continued and in July 25, 2017, Adobe published a blog post announcing that they would remove all support for Flash by the end of 2020.<sup>11</sup>

Today, Flash is a moribund technology confined to a small number of niche applications. Even legacy uses of Flash are likely to become inoperable soon for most users, as modern browsers are beginning to block Flash applications by default—a development ghoulishly reported by the tech blog Gizmodo under the heading “Google sticks another knife in Flash’s Corpse.”<sup>12</sup>

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<sup>7</sup>For example, “Steve Jobs is Lying About Adobe Flash”, <http://www.businessinsider.com/steve-jobs-is-lying-about-flash-2010-4>, Business Insider, April 30th, 2010. and Adobe Hits back at Apple’s “smokescreen”, The Telegraph, April 30th, 2010.

<sup>8</sup>Apple v. Adobe: Something Just Doesn’t Add Up

<sup>9</sup>“Flash Back: Demand Up in Engineering Specialty,” The Wall Street Journal, August 26th, 2010.

<sup>10</sup><https://www.zdnet.com/article/adobe-ditches-mobile-flash-refocuses-on-html5/>

<sup>11</sup><https://www.theverge.com/2017/7/25/16026236/adobe-flash-end-of-support-2020>

<sup>12</sup><https://gizmodo.com/google-sticks-another-knife-in-flashes-corpse-1836840400>

## 2.2 An online labor market

Our primary empirical setting for studying the demise of Flash is an online labor market. In this market, employers post job openings to which workers can apply. Employers can solicit applications by recruiting workers, or workers can just apply to openings they find. Employers then screen applicants and potentially make a hire. If a hire is made, the wage is observed, as well as the number of hours worked if the job was an hourly job. On the platform, hours-worked and earnings are measured essentially without error, as workers use a kind of digital punch clock to record hours.

Employers self-categorize job openings depending on the nature of the work. Employers also label each job opening with up to ten skills, which must match a “controlled vocabulary” of skills maintained by the platform. The controlled vocabulary of skills contains several thousand distinct skills, and new skills are frequently added (Anderson, 2017). As expected, given the platform’s focus on technical work, many of the skills are programming languages, tools, and software frameworks, e.g., Flash, PHP, C, HTML, etc.

The skills added by an employer are used by workers to find jobs that match their skills. Would-be applicants use these listed skills—as well as the category of the job opening—to decide which jobs to apply to. Workers also list skills in their own profiles. Employers can also see the details of past jobs completed by the applicant, which are labeled with the skills selected by the original employer.

The extensive skill labeling on the platform allows us to characterize a worker’s skill focus—particularly whether they used Flash. We can also use the skill labeling to characterize a change in skill focus. To do this, we take all jobs that workers had prior to TOF and compute a vector of “shares” of skills. For example, if the worker had one project that used skill A and B and another that used B and C, we would compute their share vector as  $(1/4, 1/2, 1/4)$  for  $(A, B, C)$ . As we observe applications, we can then characterize how “close” an applied-to job is to a worker’s skill history by taking the dot product of the skill vector for that job with the worker’s share vector. We call this dot product “application similarity.” For example, if the worker applied to a job that required skill B alone, the value would be  $1/2$  and if they applied to a job requiring  $D$  and  $E$ —skills they have not worked with at all, the value would be 0. As such, a lower dot product means the worker is applying to jobs farther “away” from his or her historical focus.

## 2.3 Representativeness of the market

Our samples are not the universe of all Flash workers or IT workers, and most of analysis is conducted in the context of a particular marketplace rather than *the* market (Roth, 2018). However, our evidence suggests that changes in the broader IT market are reflected in the marketplace. Existing data sources that would be representative of the whole labor market would not be appropriate for our research questions—none of the phenomena we explore would be detectable at the BLS level of occupation—for instance, our treatment and control would need to be “software developers” or “computer programmers.”<sup>13</sup> It is inevitable that statistical agency data collection elides over worker and job opening differences that are important to market participants, such as the degree of specialization as is demanded by the modern economy. But this limitation of the data should not prevent us from realizing that matching and economic decision-making is often happening at a finer scale that we typically observe (Marinescu and Wolthoff, 2016) and that case studies at the right level of granularity can be as useful as “representative” samples.

We have some ways to assess whether the online labor market is representative of the broader labor market for technical skills. Figure 1 showed a close relationship between our platform and Stack Overflow with respect to Flash popularity, though the skills being referenced on StackOverflow might be a selected sample compared to IT skills being used in the wider industry. One way to assess representativeness—at least with respect to the waxing and waning of developer interest—is to compare job openings to search engine query volume. Given the ubiquity of Google, Google search volume is likely to be the best available source to measure interest economy-wide, providing some representation of “ground truth.” Baker and Fradkin (2017) validate the idea that useful “real world” labor market information can be provided by Google search data. Unfortunately, this approach is challenging using a query on the keyword “Flash” because [the] Flash is also the name of a popular DC Comics superhero and people are less likely to type in the full form “Adobe Flash.” As one might imagine, superhero-related queries dominate software development queries on Google.

As a substitute technical skill that allows us to assess representativeness

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<sup>13</sup>See <https://www.onetonline.org/link/summary/15-1131.00>. See Bound et al. (2015) for an example of work that is possible on the IT labor market using the BLS level of occupation.

but still use Google search data, we use FBML (Facebook Markup Language), a now deprecated language for creating Facebook applications. In relatively quick succession, the technology was introduced, gained popularity, and then was replaced with a different Facebook technology. Both the rise and fall of FBML occurred during the time frame for which we have online labor market data.

In Figure 2, we plot (1) the normalized search volume on Google for FBML, (2) the number of jobs requiring FBML on our online labor market, and (3) the number of questions asked on Stack Overflow tagged with FBML. This comparison suggests that measures from all of these sources move together quite closely. The waxing and waning of the market for technologies appears to be well captured by the activity on the online labor market as well as on Stack Overflow, at least for this one example where the two indicators of market activity can be cleanly measured.

### 3 The market for Flash skills

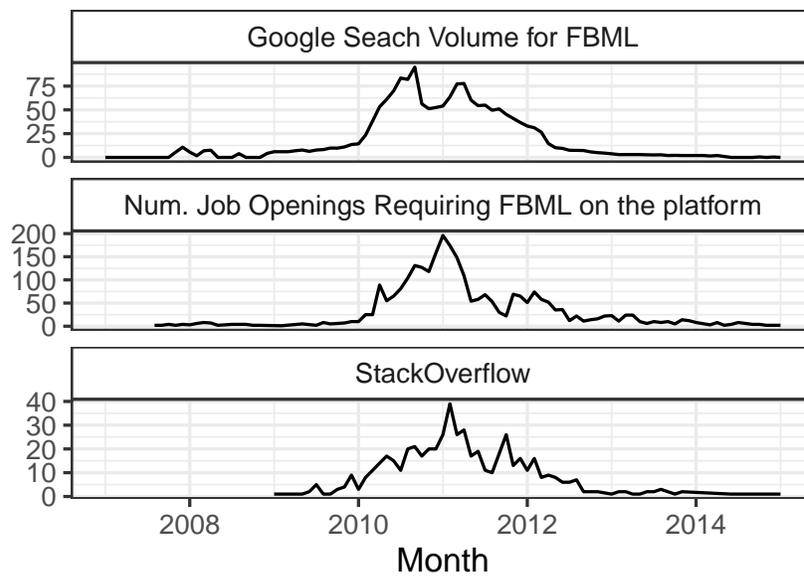
Simply plotting Flash market attributes over time illustrates some features of the decline of Flash. We first plot monthly time series of job openings that required either Flash or ActionScript. For comparison, we do the same for PHP. PHP has long been a popular server-side scripting language for creating web applications (e.g., Facebook was originally written in PHP). It is an attractive comparison technology because it was popular at the start of our time series and continued to be widely used up until the end of the panel. It is also historically the mostly commonly-requested skill on the platform with, by far, the largest volume of hours-worked, making it less likely that Flash “refugees” are affecting PHP measures. As not everything of interest can be measured at the job opening level, we also construct supply-side measures that allow us to characterize the flow in and out of Flash and the number of hours-worked per active worker.

#### 3.1 Attributes of posted job openings

A number of monthly measures at the job opening level are plotted as indices in Figure 3. The indices are scaled such that they have a mean value of 0 for the period before TOF for both Flash and PHP.

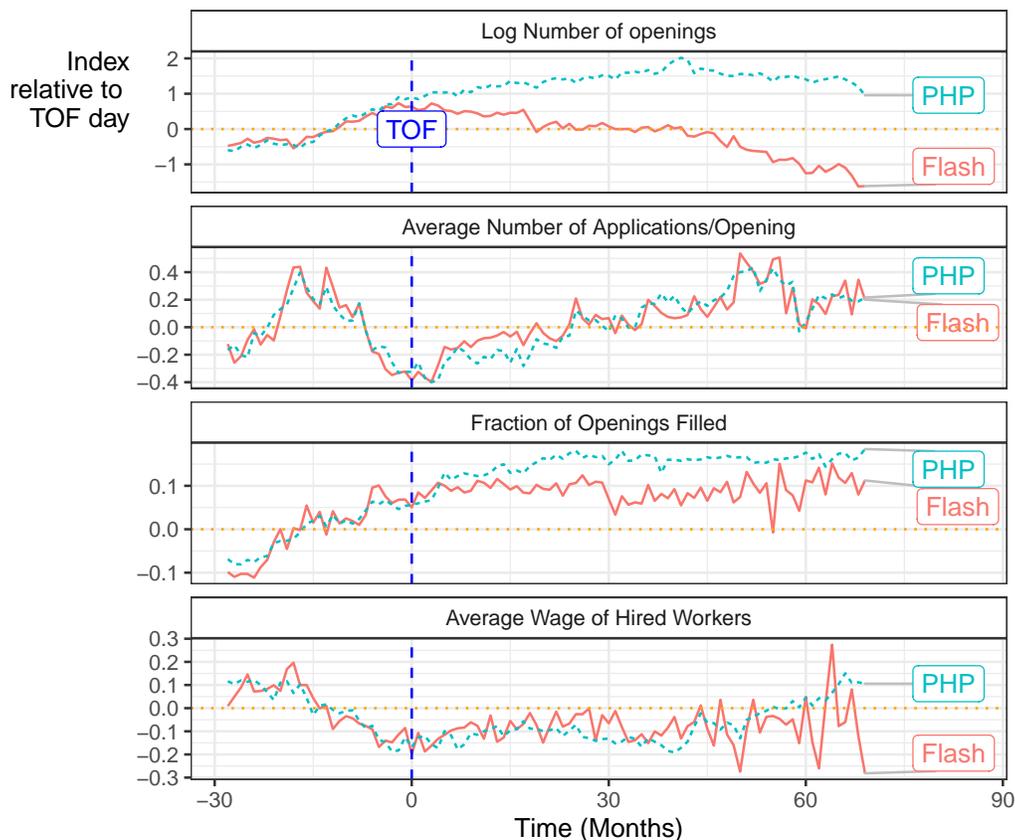
In the top facet of the figure, the log number of openings is plotted, and

Figure 2: Assessing representativeness by comparing FBML-related volume on three platforms



*Notes:* This figure shows the relative search volume for FBML on Google (top facet), job posts in an online labor market requiring FBML (middle facet), and number of questions on Stack Overflow tagged with FBML (bottom facet). The unit of time is months.

Figure 3: Attributes of Flash and PHP markets over time on the platform



*Notes:* The figure shows the a variety of per-month attributes of job openings that require either PHP or Flash. The blue line indicates TOF.

it recapitulates what we saw in Figure 1. We can see a clear decline in Flash openings following TOF. The second facet from the top is the mean of the log of the number of applications per opening. The number of applications submitted for each PHP and Flash opening track very closely even post TOF. There is no evidence that Flash jobs were over-subscribed by out-of-work Flash specialists.

Despite no apparent post-TOF change in the numbers of applicants, Flash workers may have started bidding less, allowing more openings to be “filled”—defined as the employer hiring at least one worker. This does not appear to be the case—in the third facet from the top, the measure is the

fraction of job openings that are filled, and if anything, the fill rate for Flash jobs seems to decline relative to PHP post-TOF. Again, this is the opposite of what we would expect if the decline of the Flash technology was interpreted primarily as a negative demand shock.

The conjecture that Flash workers started bidding less also does not seem to be borne out, as measured by the wage of the hired worker. In the bottom facet, we can see that average wages stay about the same relative to PHP. Near the end of the data, there are not many observations and so the estimates of the hourly earnings rate grows imprecise.

### 3.2 Attributes of workers

For our worker analyses, we constructed a monthly panel of Flash and non-Flash workers. There are 324,097 workers in the panel. Of these, the number that were active before TOF and had some Flash experience is 1,871. Flash workers are defined as those that had earned some amount of money on a Flash project before TOF. By TOF, they had collectively worked 248,491 hours on Flash projects. Some workers joined the platform post-TOF but still worked in Flash. A total of 5,640 workers worked at least some hours on Flash projects during the period covered by our data.

We plotted the number of job openings requiring Flash in Figure 3, but not the quantity of Flash hours-worked delivered. With our worker panel, we can plot hours-worked. In Figure 4a, in the bottom facet, we plot total hours-worked. We can see it peaks at TOF and then declines. In the middle facet, the output is the total number of Flash workers active that month, with “active” defined as working at least some number of hours. It also peaks near TOF, but it seems to decline more steeply compared to the total hours-worked plot.

A greater relative decline in numbers of workers than in hours is borne out in the top facet of Figure 4a, which plots hours-worked per active worker. We can see that it was about 40 hours per-month at TOF but then rises post-TOF, rising to nearly 60 hours per-month.<sup>14</sup> In contrast to a view in which existing projects are split over more workers, we instead see greater concentration of the available hours in some developers on the platform.

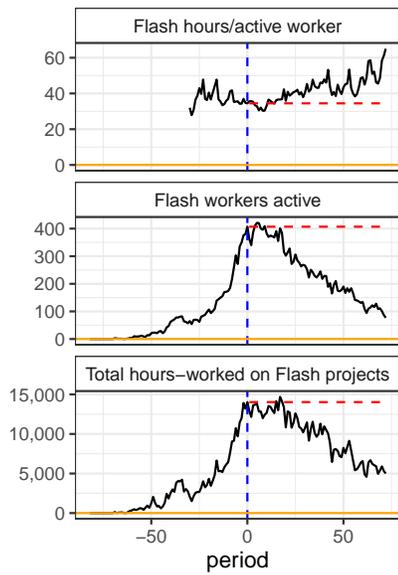
To explore the flow of workers in and out of Flash, we calculate the first

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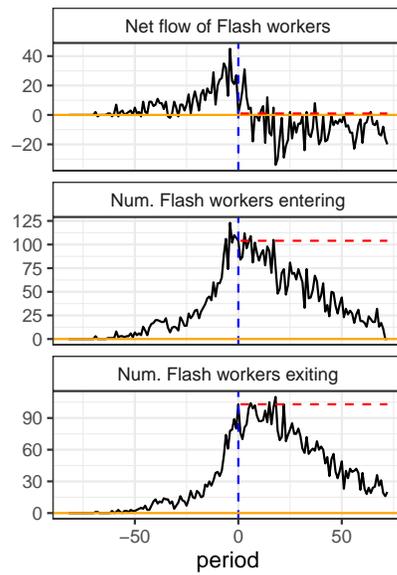
<sup>14</sup>We do not plot early values of this ratio, as the market was relatively small and the estimate of hours-per-worker is imprecise.

Figure 4: By-month grand means for all Flash workers

(a) Hours-worked



(b) Entry/exit



*Notes:* This figure shows the weekly time series of a number of attributes of workers active in Flash. The blue line indicates TOF. The dotted red line indicates the mean value of the attribute at TOF.

and last months a worker worked on a Flash project. We then plot the number exiting (bottom facet), entering (middle facet), and the net flow (top facet) in Figure 4b. Prior to TOF, the flow is positive but it turns negative shortly after. The flow of workers out of Flash reaches a maximum about 5 months after TOF.

The patterns in Figure 4 suggest that a change in Flash hours was better explained by some workers entirely abandoning Flash projects and other workers staying with it, rather than an even decline in Flash activity across all Flash workers.

### 3.3 What happened next in the product market?

Although our focus is on the supply side of the market, a natural question is where the demand for Flash “went.” The product market niche for interactive, online, graphics-heavy applications that Flash occupied did not disappear post-TOF. Post-Flash, HTML5 and CSS3 were widely viewed as the successor technologies to Flash.<sup>15</sup> Indeed, we can see in our data that Flash jobs being posted post-TOF increasingly reference HTML5 as another skill required—about 20% of Flash jobs at TOF already mentioned HTML5, and by the end of our panel, more than 30% mentioned HTML5.<sup>16</sup> We cannot tell from the project data parameters if these are conversion projects requiring developers to know both Flash and HTML5 or alternatively, projects in which developers can use either of the two technologies. Nevertheless, the fraction of applications to projects listing both was clearly rising.

## 4 Economics of a decline in demand for a skill

Having presented some of the key stylized facts about how the market for Flash skills evolved, we take a step back to discuss the economics that could explain these facts. If we assume a single labor market for Flash skills and

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<sup>15</sup>For example, Amazon used HTML5 and CSS3 for book previews—something they would have done with Flash earlier: “Amazon also plans to release the feature using HTML 5 and CSS3, the latest Web standards that are sometimes being used as an alternative to Adobe’s Flash for interactive online experiences.” Bilton, Nick (June 30, 2010). “Amazon to Introduce Web-Based Book Previews”. Bits. The New York Times. <https://bits.blogs.nytimes.com/2010/06/30/amazon-to-launch-web-based-book-previews/>.

<sup>16</sup>See Appendix B.1.

set aside any elaborations about dynamics, a decrease in demand should not increase the quantity of hours-worked and it should not increase wages. At least one—hours-worked or wages—should fall, though the amount depends on the elasticity of the supply curve. Empirically, we observe a decline in hours-worked (bottom facet of Figure 4b), but no decline in wages (bottom facet of Figure 3). This outcome could occur if workers are infinitely elastic in their labor supply to the Flash market.

A near infinite labor supply elasticity seems improbable for a skill that requires a significant human capital investment—it would imply that Flash specialists have some other non-Flash skill that they are just as productive in and can readily switch to. This is hard to square with any gains to specialization in this market. Furthermore, we also show, empirically, that there are substantial gains to skill specialization.

As an alternative, consider a market supply curve consisting of the schedules of a collection of workers of different “vintages” planning to work for multiple periods. These workers value experience in the present for the human capital it imparts, which will be valuable in the future. With this dynamic perspective, a negative demand shock could be met with a supply response other than movement along the supply curve: would-be entrants switch to other skills with more of a “future” and some incumbents with a long-enough horizon exit. This could create a highly elastic market supply curve—or even shift the curve in so that wages actually rise—despite costly switching and workers having “standard” labor supply elasticities to the labor market as a whole. We make this argument more precise with a simple model that bears some similarities in spirit to [Artuç et al. \(2010\)](#), which estimates a model of switching costs inferred from labor flows in response to trade-shocks.

## 4.1 A simple model of skill obsolescence and transition

Workers use some skill to produce an output. Workers live two periods and have a discount factor of  $\beta < 1$ . In the first period, they are still learning the skill and have productivity  $y < 1$ , and get paid  $yw$ , where  $w$  is the market wage in efficiency units. If incumbents keep working in that skill in the second period, they have productivity 1 and earn the “full” wage  $w$ . We will refer to workers that have already worked a period as “incumbents” and those that are first entering the market as “entrants.” An incumbent who switches skills in their second period only has productivity  $y$  in that new skill, and never gets to be experienced. We assume there is an intensive margin elasticity

of supply:  $S(w) = wn$  where  $n$  is the measure of units of productivity in that market (i.e., each entrant worker provides  $y$  and each incumbent worker provides 1). Providing any amount of output is sufficient to raise a worker's personal productivity from  $y$  to 1.

There are two skills, A and B. The A skill market is small, and the B skill market is vast, in the sense that if all A workers joined the B skill market, the wage in the B skill market would not change. Each market has completely inelastic demand.

The two markets have been in a steady state, with a measure of 1 workers joining the A market each period. If both incumbents and entrants are in a skill market, they have aggregate production  $n = 1 + y$ . Demand in A was 1 prior to the shock. Market clearing requires  $S(w_A^0) = w_A^0(1 + y) = 1$ , where  $w_A^0$  is the pre-shock wage. For entrants to be indifferent between A and B, pre-shock, as required in a steady-state,  $w_A^0 = w_B$ , where  $w_B$  is the pre-shock wage in B and so  $w_B = 1/(1 + y)$ .

From a steady state, demand in A then experiences a foreseeable shock, in the sense that workers can see two periods of demand coming up: the demand will be  $d$  in the next period, with  $d < 1$  and 0 the period after that. The wage in A when demand in the period is  $d$  will be  $w_A^1$ , which is endogenous. In the period after that, the market will no longer exist.

Would-be A entrants have to decide whether to enter A and earn  $yw_A$  initially, and then  $\beta yw_B$ , (working a period in A and then moving to B) or to start their careers in B, earning  $yw_B$  and then  $\beta w_B$ . Incumbents in A have to decide whether to stick with A and earn  $w_A$  or switch to B and earn  $yw_B$ . It is clear that if entrants choose to enter A in spite of the impending fall in demand, it must be because  $w_A$  is higher than  $yw_B$ .

First consider the scenario where some entrants still choose to enter A and all incumbents stick with A. Let the fraction of new entrants choosing A to be  $x$ , with  $1 - x$  choosing B, but because B is vast,  $w_B$  is unchanged by the influx. Market clearing in A is now  $w_A^1(1 + yx) = d$ . As all new entrants have the option of choosing B, incentive compatibility requires that entrants are indifferent, or  $yw_A^1 + y\beta w_B = yw_B + \beta w_B$ , which we can re-write as

$$\frac{w_A^1}{w_B} = 1 + \left( \frac{1 - y}{y} \right) \beta.$$

Let  $\overline{w_A}$  be the A skill wage that satisfies this constraint. Note that  $\overline{w_A} > w_B$ , implying that wages *rise* in the dying skill.<sup>17</sup>

<sup>17</sup>Though we should expect this effect to be tempered by demand curves being sloped

Now consider a scenario with a larger shock to demand. All new entrants switch to the new technology, but no incumbents switch. However, because employers are completely inelastic, the wage in A falls until incumbents are indifferent between switching or staying, i.e.,  $w_A^1 = yw_B$ . Note that the larger the  $y$ —i.e., the smaller the cost of learning the skill—the less the wage declines in the dying skill. This creates a discontinuity in the A wage. Before it was pinned down by the new entrants, but now it is pinned down by the incumbents.

Now consider an even larger shock, such that at least some incumbents must exit for the market to clear. Let  $z$  of the incumbents switch and all the new entrants choose B. Market clearing in A is  $zw_A^1 = d$ . As all incumbents have the option of choosing B, incentive compatibility implies that  $w_A^1 = yw_B$ . Let  $\underline{w}_A$  be this wage in A that satisfies incentive compatibility.

To summarize, there are three possible equilibria that depend on the size of shock:

1. For  $d > \overline{w}_A$ , the wage will be  $\overline{w}_A$  and some entrants still choose A, getting a premium in their first period.
2. For  $\underline{w}_A < d < \overline{w}_A$ , all entrants choose B but all incumbents stick with A. The market wage is  $\underline{w}_A = yw_B$ , or the wage of the novice B worker.
3. For  $d < \underline{w}_A$ , even some incumbents choose to switch, but with the wage also staying at the novice B worker level,  $\underline{w}_A = yw_B$ .

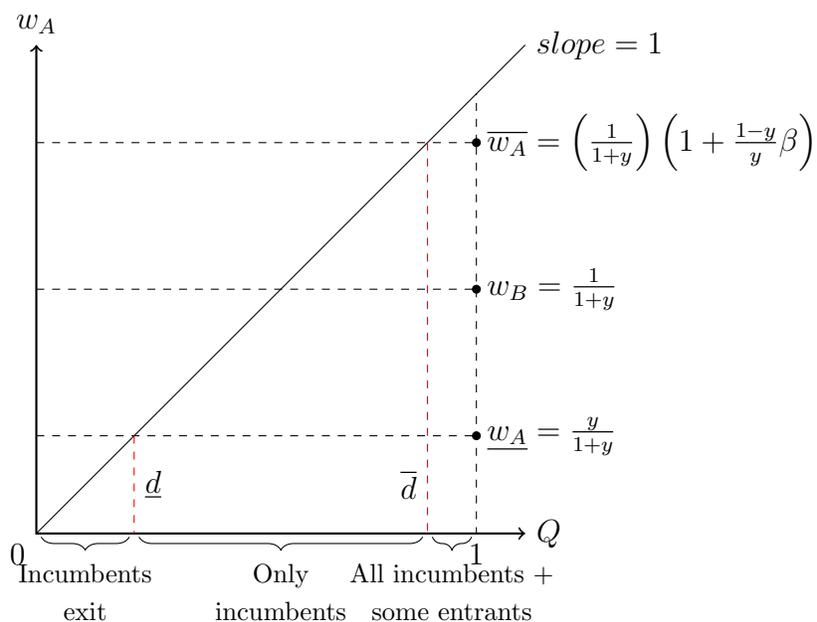
The possible equilibria as a function of the size of the demand shock are shown in Figure 5. The x-axis is the quantity of labor in the A market (in efficiency units) during the  $d$  period; the y-axis is the wage in the A market during the  $d$  period. The wage in the B market,  $w_B$ , is  $1/(1+y)$ . The two relevant wages,  $\overline{w}_A$  and  $\underline{w}_A$ , are plotted as horizontal lines. If the demand level is greater than  $\overline{d}$ , the market clears by only  $x$  of the would-be entrants choosing A. Below  $\overline{d}$  but above  $\underline{d}$ , the market clears by all incumbents staying in the market but reducing their output on the intensive margin and the wage being  $\underline{w}_A$ . For levels of demand below  $\underline{d}$ , the market clears by some incumbents choosing to exit.

As  $\beta$  increases (i.e., workers value the future more), we have a higher  $\overline{w}_A$ , so entrants need a larger premium in A to not switch. This also means that

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rather than vertical, as we assume.

Figure 5: Demand shocks and possible equilibria



*Notes:* The x-axis is the quantity of labor in the A market during the  $d$  period; the y-axis is the wage in the A skill market during the  $d$  period. The wage in the B market is  $w_B$  is indicated and is  $1/(1+y)$ . The two relevant wages,  $\bar{w}_A$  and  $w_A$ , are plotted as horizontal lines. If the demand level is greater than  $\bar{d}$ , the market clears by only  $x$  of the would-be entrants choosing A. Below  $\bar{d}$  but above  $d$ , the market clears by all incumbents staying in the market but reducing their output on the intensive margin and the wage being at  $w_A$ . For levels of demand below  $d$ , the market clears by some incumbents choosing to exit.

the region where entrants are indifferent shrinks. As the  $w_A$  is pinned down with incumbents that have no future,  $\beta$  is irrelevant for very large demand shocks. Although the quantity is increasing in  $d$ , the wage only changes once, at  $d = \bar{w}_A$ .

For a larger  $y$ ,  $\bar{w}_A$  decreases, but  $w_A$  increases. The two different effects reflect the different perspectives of incumbents and entrants. For entrants, a higher  $y$  means the forgone benefit of being experienced in B in the next period is lower, and so a relatively lower  $w_A$  wage is needed to keep the worker indifferent. For incumbents, a higher  $y$  means jumping to B is less costly, and so a higher wage in A is needed to keep them from moving.

Returning to the data from our Flash context, the fact that we observed large reductions in hours-worked but flat wages and some evidence of continued entrance by workers post TOF, seems consistent with the “small shock” equilibria i.e.,  $d > \bar{d}$ . Of course, the actual situation is not the stylized two period world represented in the model, and the wages in the “B” market are relevant to the adjustment decisions of Flash incumbents.

In the model presented, gaining skills in A does not help in B—this is surely a over-simplification, particularly in our empirical context, where knowledge in Flash is likely to teach programming and graphic design skills that can be transferred to other contexts. In a later section, we relax the assumption that workers must “pick a single skill” and investigate how workers with skills in multiple areas were affected by the decline in Flash.

## 5 Choices and outcomes of individuals

Returning to the data, we switch our focus away from the Flash market as a whole and explore the outcomes of individual workers active prior to TOF, who we can think of as the “incumbents” in the model.

Our goal will be to compare the trajectories and choices of workers with Flash experience to a counterfactual group of workers who were not specializing in Flash. As a comparison group, we could simply use all active workers, but given that the market is fairly divided into technical and non-technical work with large associated differences in hourly earnings (Horton, 2017), this approach would tend to mix workers that are not truly comparable. Instead, we use a matching approach to construct a sample of comparable workers, and then we proceed with a standard panel analysis, using both a worker/time fixed-effects specification in both a “static” and distributed lag specification

(Borusyak and Jaravel, 2016).

## 5.1 Identification and the nature of the treatment

To identify the effects of TOF on Flash workers, we use non-Flash workers as counterfactuals for all outcomes. Our baseline identifying assumption is that, conditional upon worker and time-fixed effects, Flash workers are observationally equivalent to workers in the control group. This assumption is analogous to the one made in the literature on the effects of job loss (von Wachter et al., 2009; Couch and Placzek, 2010; Jacobson et al., 1993). In our setting, because we have a measure of Flash concentration, we can allow effects to differ based on how focused workers were on Flash pre-TOF. This is in contrast to the displacement literature where job loss is binary.

If we can obtain a sample of counterfactual workers, all that should differ is exposure to the “treatment” which is having a technical skill that is put on a path towards zero demand. It is important to note that the realized treatment—the actual effects on the demand for Flash at the actual pace observed—is inherently a fact particular to our setting. It is easy to imagine other skills being made obsolete more or less quickly, which in turn could prompt quantitatively or even qualitatively different responses. Our view is that elucidating in detail one particular example and focusing on the economic mechanisms is the only viable path towards generalizability.

In studies of displaced workers, the consensus view seems to be that the fixed effect approach works best with long observation windows and relatively mature workers whose hourly earnings likely reflect their market earnings potential (von Wachter et al., 2009). We have some insight into a worker’s age and off-platform experience (which we will discuss), but in this market, the short duration of projects and the lack of other factors that could affect earnings (amenities, benefits, relational contracts, etc.) implies that worker productivity is frequently “marked to market.” We have a relatively long panel, and so we can observe workers for some time prior to TOF, though as we saw earlier, entry was peaking just prior to TOF.

## 5.2 Construction of a matched sample

We take all workers who were active on the platform at TOF, with “active” defined as having worked at least 40 hours on platform before TOF. We indicate those workers with Flash experience with a binary indicator,

ANYFLASH. We also record the fraction of their total hours-worked that were in Flash, which we denote `FRACFLASH`. The mean value for `FRACFLASH` is about 25%.<sup>18</sup> This is likely a lower bound, as some employers do not label their openings with skills, but rather, discuss them in the job text.

We match the Flash workers to a control group of non-Flash workers (those with no pre-TOF Flash experience) (Sekhon, 2011). For matching, we construct a cross-sectional dataset by computing worker-level summary statistics at TOF, including (1) platform tenure, (2) average wage, (3) cumulative hours-worked, (4) cumulative earnings, and (5) cumulative number of applications sent. We break up the matching into quartiles by Flash pre-TOF Flash focus.

In Table 1 the two samples are compared. Panel A reports details about the full distribution, while Panel B reports t-tests for the means. As the table makes clear, we obtain excellent balance on the covariates we match on. In Appendix B.2, we plot the full distributions for each covariate. With these cross-sectional matches, we then restrict our monthly panel to only those treated workers and their matched counterparts.

As our samples are drawn from a marketplace, a natural concern is how these two groups interact, potentially creating a SUTVA violation (Blake and Coey, 2014). As we can observe all applications, we can characterize the degree to which the two groups were competing. In over 70% of openings, there was no overlap in applicants—in the remainder where there was some overlap, there was typically just one applicant from the other group. As workers send many applications and at least some Flash developers have at least some non-Flash skills, this speaks to how “clustered” this market is by skill. Furthermore, this “overlap” fraction falls over time, contrary to the notion that out-of-work Flash developers were crowding out workers in the control group. One of the reasons why SUTVA is unlikely to be a first order concern is that the Flash sample was relatively small compared to the market as a whole—at the time of TOF, the total number of workers who had applied to at least one job was over 250,000.

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<sup>18</sup>For `FRACFLASH`: the min is 0.01 and the max is 1; the 25th, 50th and 75th percentiles are 0.045/0.131/0.34; the mean is 0.25 and standard deviation is 0.28.

Table 1: Comparison of the matched samples

Panel A: Summary statistics

	N	Min	Mean	Median	Max	StDev
Total billed hours-worked						
Non-Flash	1,342	0	821	360	9,351	1,173
Flash	1,397	0	829	397	9,280	1,185
Number of organic apps						
Non-Flash	1,342	0	387	222	2,985	456
Flash	1,397	0	406	232	5,240	484
Total tracked hours-worked						
Non-Flash	1,342	0	738	331	9,172	1,045
Flash	1,397	0	721	355	8,660	991
Hourly earnings						
Non-Flash	1,342	0	11,148	4,169	168,534	19,148
Flash	1,397	0	11,671	4,607	255,585	20,940

Panel B: Means comparisons

	Means		Difference		
	Flash	Non-Flash	Diff.	SE	t-stat
Total billed hours-worked	829	821	7.9	45.1	0.2
Number of organic apps	406	387	19.4	18.0	1.1
Total tracked hours-worked	721	738	-17.4	39.0	-0.4
Hourly earnings	11,671	11,148	522.9	766.2	0.7

*Notes:* This table reports group summary statistics for several worker attributes at TOF, as well as a t-test comparing those means.

### 5.3 Time series for the matched sample

Although only matched on a cross-sectional dataset of what workers “looked like” on TOF, we can compare the matched samples over-time, pre-TOF. If the two groups moved similarly pre-TOF, it suggests that the groups are truly comparable. In Figure 6, we plot the monthly averages for treated and control workers, demeaning each worker by their pre-period mean, and then demeaning each aggregated series with the value at TOF (so each series mechanically has a value of 0 for that period). Focusing on the pre-period, we can see that Flash and Non-Flash samples move together for all outcomes.

Post-TOF, the groups begin to diverge on some measures, previewing some of our main regression results—this concordance is unsurprising but reassuring, given that our demeaning and averaging essentially re-create the regression mechanics. In the top facet we see there is no evidence of a decline in average wages for Flash workers. It is important to note that this is the average wage for all kinds of work, including both Flash and non-Flash projects. Although there is no evidence of a wage decline, in the facet below, there is some evidence of a decline in hours-worked. This decline comes despite evidence of an increase in applications sent, which we can see in the third facet from the top. In addition to perhaps increasing application intensity, there is also evidence of a move away from skills relied on in the past: in the bottom facet, we see that Flash workers begin applying to jobs that are less like their previous jobs, skill-wise. Interestingly, there is also a decline in similarity for non-Flash workers, consistent with the [Deming and Noray \(2018\)](#) claim of frequent STEM obsolescence.

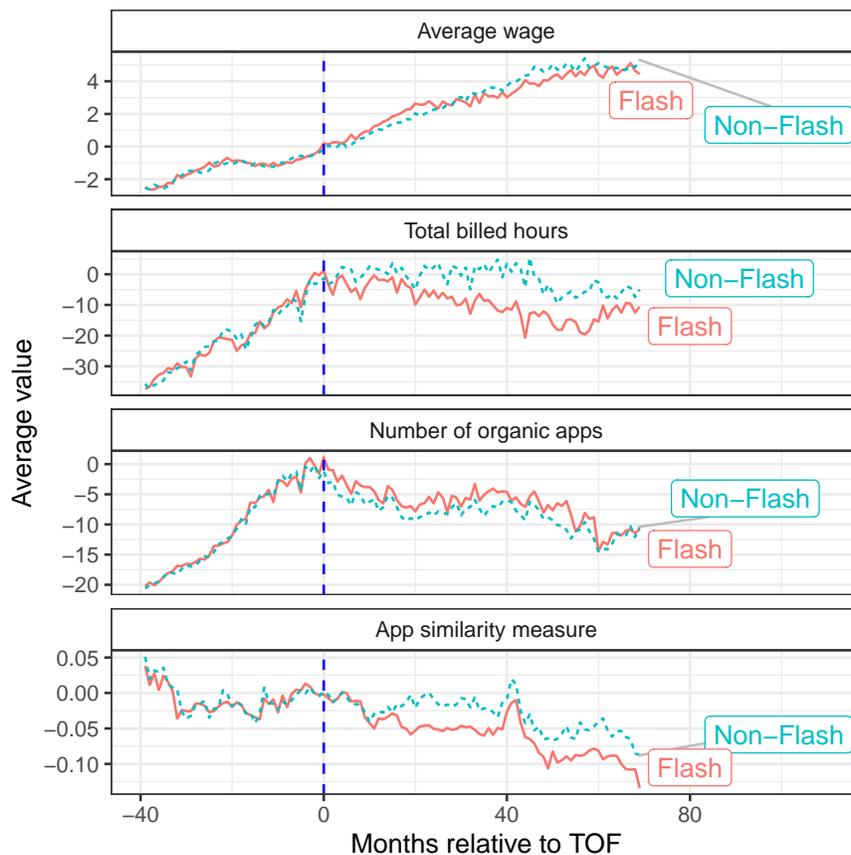
### 5.4 Estimates of the effects of TOF on Flash workers

To obtain estimates of the effects of TOF, using our matched panel, we estimate the model

$$y_{it} = (\text{ANYFLASH}_i \times \text{POST}_t) \beta + \gamma_i + \delta_t + \epsilon_{it}. \quad (1)$$

where  $y_{it}$  is an outcome of interest for worker  $i$  at period  $t$ ,  $\text{POST}_t$  is an indicator for whether the period was after TOF, and  $\text{ANYFLASH}_i$  is an indicator for whether the worker has worked in Flash prior to TOF. The  $\gamma_i$  represents a full set of worker fixed effects, which will absorb the impact of time-invariant worker characteristics. The  $\delta_t$  represents a full set of period fixed effects. The error term,  $\epsilon_{it}$ , includes all other time-varying unobservable shocks to the

Figure 6: Matched sample monthly averages for treatment and control groups, demeaned



*Notes:* This figure plots the monthly averages for workers from our matched sample. Before calculating each monthly average, we demean each worker's value by their pre-TOF value. From these monthly means, we subtract the value on TOF month so that each series has a value of 0 in that period.

worker’s outcome in that period. The  $\beta$  coefficient is interpretable as the average effect of the TOF on Flash over the full post-period.

We can also allow the effects of TOF to depend on how focused the worker was on Flash pre-TOF. For each worker, we compute the fraction of hours-worked that were spent on Flash projects,  $\text{FRACFLASH}_i$ . This is zero for the control group. We can interact this measure with the post indicator by creating an independent variable  $\text{FRACFLASH}_i \times \text{POST}_t$ . This changes the interpretation of  $\beta$  to a measure of the effect for workers spending 100% of their time on Flash projects, with effects linearly scaled down for workers less-focused on Flash.

Our preferred specification is to restrict the panel to Flash workers who (a) have at least 1% of their pre-TOF hours in Flash (b) have at least 40 hours of platform work in total and (c) work in at least two distinct months prior to TOF. We also truncate the end of the panel by one quarter, as some panel measures are “incomplete” near the end of our data. We also truncate the start of the panel to 40 months before TOF because this corresponds to the true launch of the platform (nearly the entire sample joined the platform after this date). We restrict hourly wages to be positive and less than \$100/hour—this removes a very small number of observations that likely reflect users who were not on *bona fide* hourly contracts but were instead using the time-tracking features of the platform or were using lump sum payments but billed them as hours-worked. We report point estimates using other sample definitions as well as alternative panel specifications in Appendix B.3, which shows that our estimates are not sensitive to these choices.

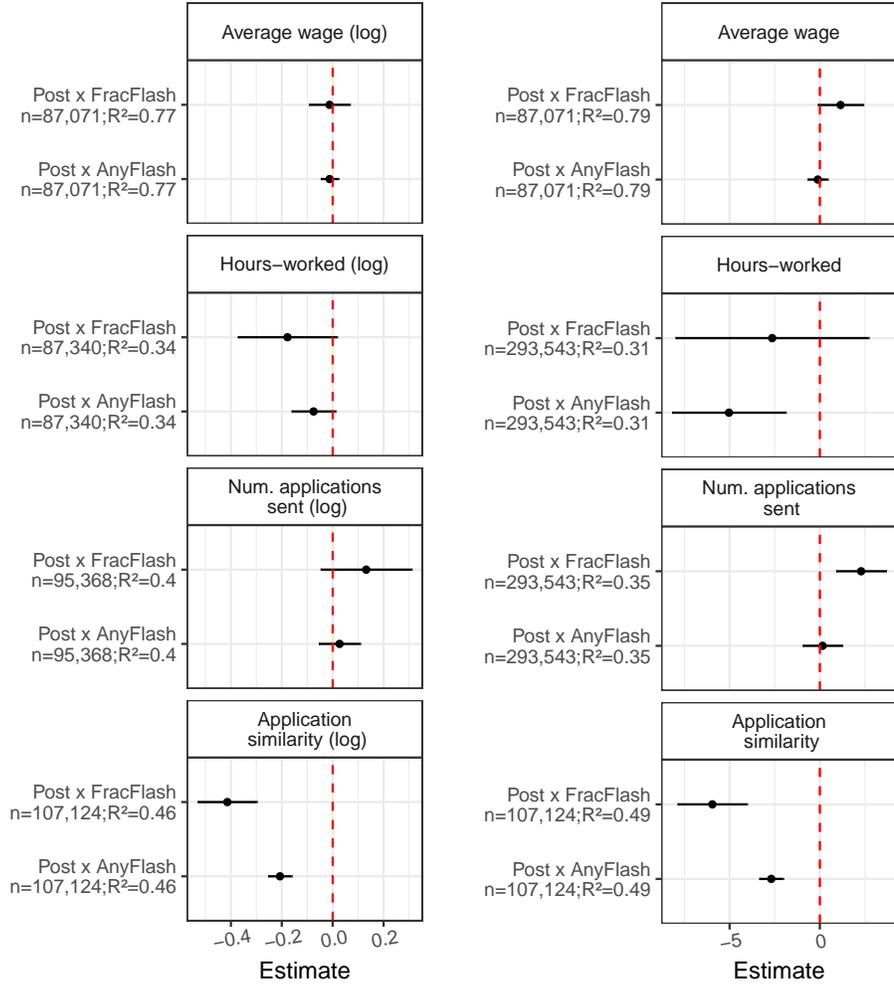
A first question is whether the workers were differentially likely to be active on the platform. We find no evidence that they differed from the control on several definitions of “exit”—this analysis is reported in Appendix B.4.

In Figure 7, we report estimates of  $\beta$  from Equation 1, for both independent variable specifications ( $\text{ANYFLASH}$  and  $\text{FRACFLASH}$ ). The left facet outcomes are in logs with zeroes removed, in Figure 7a, whereas the right facet outcomes are in levels, in Figure 7b. Mirroring Figure 6, the outcomes from top to bottom are average wages, hours-worked, number of applications sent, and application similarity. In all regressions, standard errors are clustered at the level of the individual worker. The regressions are run with unbalanced panels when the outcome cannot be computed (such as an average wage or application similarity measure if the worker did not work or send any applications that period, or when the outcome is the log of a count, such as hours-worked).

Figure 7: Effects of TOF on Flash worker outcomes

(a) Log outcomes

(b) Level outcomes



*Notes:* This figure reports estimates of  $\beta$  from Equation 1. We estimate models in which there is a single treatment indicator, ANYFLASH, and models where the independent variable is FRACFLASH, which is the fraction of pre-TOF hours-worked that were on projects requiring Flash. Sample sizes for each regression are reported under the point estimates. Differences in sample sizes reflect the fact that the panel is unbalanced.

In the top facet, the outcome is the average wage (in logs in Figure 7a and levels in Figure 7b). For average wages in logs, we can see the effect of TOF was a precise zero for both specifications—there is no evidence of a decline in hourly wages for Flash workers. This matches what we observed in Figure 6. In levels, there is some evidence that the most experienced Flash developers had an increase in average wages—the FRACFLASH specification is positive and nearly significant.

In the second facet from the top, the outcomes are log hours-worked and hours-worked. Every point estimate is negative. In logs, the ANYFLASH specification point estimate is about 10% fewer hours, whereas the FRACFLASH estimate is 20% fewer hours-worked. Given that more Flash-focused workers had to make a larger transition, skill-wise, this could reflect a greater difficulty in finding work, assuming preferences have not changed and this is not an intensive margin response to changed wages. In levels, we also observe a decline but the magnitudes are “switched” with a larger reduction in the ANYFLASH specification, though both estimates are fairly imprecise.

In the second facet from the bottom, the outcome is the log number of applications sent and the number of applications sent. For the number of applications sent, which is a measure of job search effort, we can see that point estimates are always positive, though for the ANYFLASH group the estimates are close to zero. For the FRACFLASH group log regressions, the estimates imply about a 10% increase, conditional upon sending any applications. For the ANYFLASH group, the point estimate is close to zero. Workers who were highly specialized in Flash sent more applications post-TOF.

In the bottom facet, the outcome is application similarity (scaled from 0 to 100). There is a marked decline for Flash workers in all specifications. The effects are stronger in the FRACFLASH group, implying that those workers most specialized in Flash had to make the largest adjustments in application focus.

## 5.5 Estimates of the dynamic effects of TOF on Flash workers

Rather than assuming a single effect as in Equation 1, we can estimate a distributed lag model. The benefit of this specification is that we can trace out the evolution of adjustments. The drawback is that we have more parameters

to estimate. We estimate

$$ny_{it} = \sum_{k=-a}^b (\text{POST}_{ik} \times \text{ANYFLASH}_i) \beta_k + \gamma_i + \delta_t + \epsilon_i, \quad (2)$$

where  $\text{POST}_{ik}$  is the value of the post indicator  $k$  months away, using  $a = 12$  and  $b = 24$  to give us a one year pre-period and a 2 year post period.

Cumulative effects for our outcomes (in levels) are plotted in Figure 8, imposing a restriction that cumulative effects on  $t = -1$  are zero and using the covariance matrix to construct confidence intervals. We also plot effects using `FRACFLASH` instead of `ANYFLASH`.

In Figure 8, we can see that across outcomes, the `FRACFLASH` estimates are less precise than the `ANYFLASH` estimates. Reassuringly, there is no graphical evidence of pre-trends for any outcome, for either specification.

In the top facet, the outcome is the average wage. Matching our static estimates, there are no effects on average wages with the `ANYFLASH` specification and perhaps some limited evidence of an *increase* in wages in the `FRACFLASH` specification.

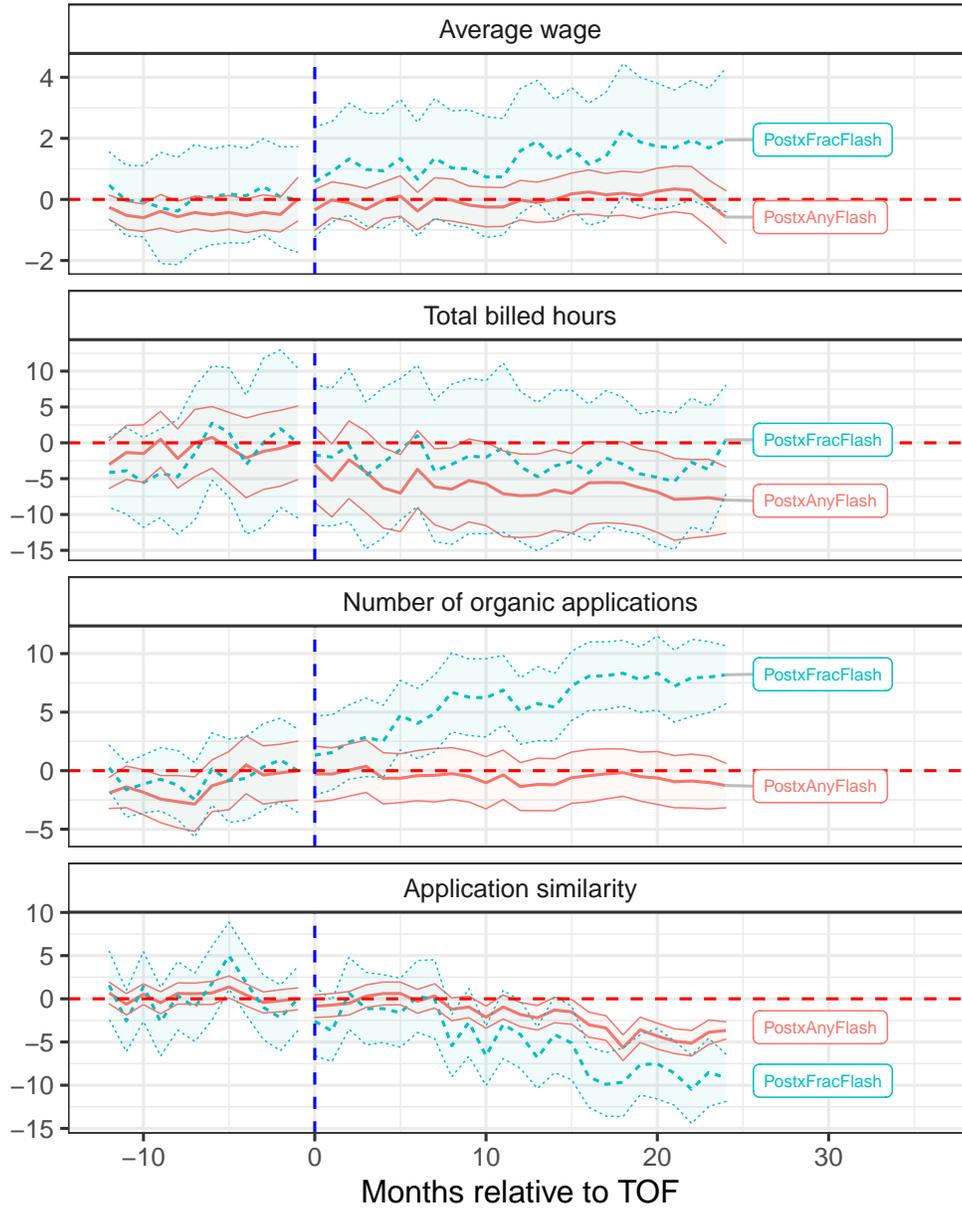
In the second facet from the top, the outcome is hours-worked. For both `FRACFLASH` and `ANYFLASH`, total hours-worked are lower, matching what we observed in the static estimates. The estimates are imprecise and the confidence intervals frequently include zero. Furthermore, there is no clear temporal pattern, and particularly no evidence that the gap shrinks by the end of the period.

For application intensity, matching the static results, we see large increases in application intensity, but only in the `FRACFLASH` specification. The increase in intensity occurs shortly after TOF and stays consistently higher. In contrast, for the `ANYFLASH` group, the effects appear flat and are quite close to zero.

For application similarity, there is a post-TOF decline with both specifications, though effects are larger in the `FRACFLASH` specifications. The movement away from Flash is not right after TOF, only turning clearly negative about 8 months later, which is right around the Android “Jellybean” announcement. Note the larger effects for `FRACFLASH`. This is not mechanical, as we could have seen these incumbents, who were more focused on Flash, being disproportionately likely to “stay” in Flash, producing a high similarity measure.

We also estimate dynamic panel data models, allowing worker outcomes

Figure 8: Distributed lag model estimates of TOF effects



Notes: This figure reports estimates of cumulative effects from Equation 2.

to depend on based values of the outcome, which give long-run effects very similar to the static specifications. This analysis is in Appendix [B.5](#)

## 5.6 Flash-specific experience matters

Perhaps the reason for little fall-off in wages for Flash workers was that they had some other skill that they were just as productive in, perhaps because experience in Flash also helps in other skills. In the model presented in Section [3](#), gaining skills in A does not help in B—but this is surely an over-simplification, particularly in our empirical context, where knowledge in Flash is likely to teach more general programming and graphic design skills.

Instead of our stark “pick a single industry” assumption, we could allow workers to split a unit of time between A and B, spending  $t_A$  in A and  $1 - t_A$  in B, leading to human capital in the second period of  $z_A$  and  $z_B$  respectively. Work in one skill would translate into human capital at a rate  $1 - y$  in that skill, and a rate  $\alpha < 1 - y$  in the “other” skill, under the assumption that the best experience in a skill is actually working in that particular skill. This would create an investment frontier, as in [Murphy \(1986\)](#), defined by

$$\begin{aligned} z_A &= (1 - y)t_A + \alpha(1 - t_A) + y \\ z_B &= (1 - y)(1 - t_A) + \alpha t_A + y. \end{aligned}$$

As in [Murphy \(1986\)](#), risk neutral workers pick a corner solution specializing in A or B, but the higher the value of  $\alpha$ , the lower the cost of transition—at  $\alpha = (1 - y)$ , learning would be the same in both, making it irrelevant which skill was chosen.

Empirically, learning Flash could make developers productive in other, related skills. In a typical setting, such spillovers would be challenging to estimate for [Roy \(1951\)](#) model reasons, as we would not see workers working in both Flash and non-Flash. However, in our context, we do see non-Flash workers working in other skills: the treated group in our sample did work in other skills at observable hourly wages—for no worker is  $\text{FRACFLASH} = 1$ . Using only the treatment group of Flash developers, we can estimate the wage-tenure curve for hours of experience in Flash and non-Flash hours-worked for both Flash wages and non-Flash wages, using the panel. The two

regressions are

$$\begin{aligned}\log w_{Non-Flash} &= \beta_{BA} \log H_{Flash} + \beta_{BB} H_{Non-Flash} + \delta_t + \gamma_i + \epsilon \\ \log w_{Flash} &= \beta_{AA} \log H_{Flash} + \beta_{AB} H_{Non-Flash} + \delta_t + \gamma_i + \epsilon.\end{aligned}$$

In Column (1) of Table 4, we see that returns to experience are positive and significant, but that “own-skill” returns are always greater. If we counterfactually assume that Flash workers could have re-allocated all of their pre-TOF hours of experience into non-Flash work, they would have had, on average, 39% higher wages in non-Flash skills at TOF.

Table 4: Returns to hours-worked in Flash and Non-Flash jobs

	<i>Dependent variable:</i>	
	Non-Flash Log Wage	Flash Log Wage
	(1)	(2)
Cumulative Flash hours	0.021*** (0.003)	0.019** (0.006)
Cumulative Non-Flash hours	0.031*** (0.005)	0.014* (0.007)
Week FEs	Y	Y
Worker FEs	Y	Y
Observations	15,373	5,442
R <sup>2</sup>	0.797	0.920

*Notes:* This table reports estimates of the effects of project experience on post-TOF wages for Flash and non-Flash projects. Significance indicators:  $p \leq 0.10$  : †,  $p \leq 0.05$  : \*,  $p \leq 0.01$  : \*\* and  $p \leq .001$  : \*\*\*.

The results are not consistent with Flash experience leading to human capital that is just as valuable in some other non-Flash skill area. There are spill-overs, but it is not the case experience is completely general, and so we expect Flash specialists to be relatively disadvantaged.

## 6 Individual heterogeneity in adjustment

Several factors can affect a worker’s decision about whether to stay with Flash or to switch, including the extent of their specialization with the skills

and the cost borne when switching to a new skill. Workers with a longer career horizon have more of an incentive to switch away from Flash. Workers with “better” fall-back skills in their portfolio might also switch more quickly. All of these except age are missing from our stylized model, but it is easy to imagine they are empirically important.

## 6.1 Worker career horizon

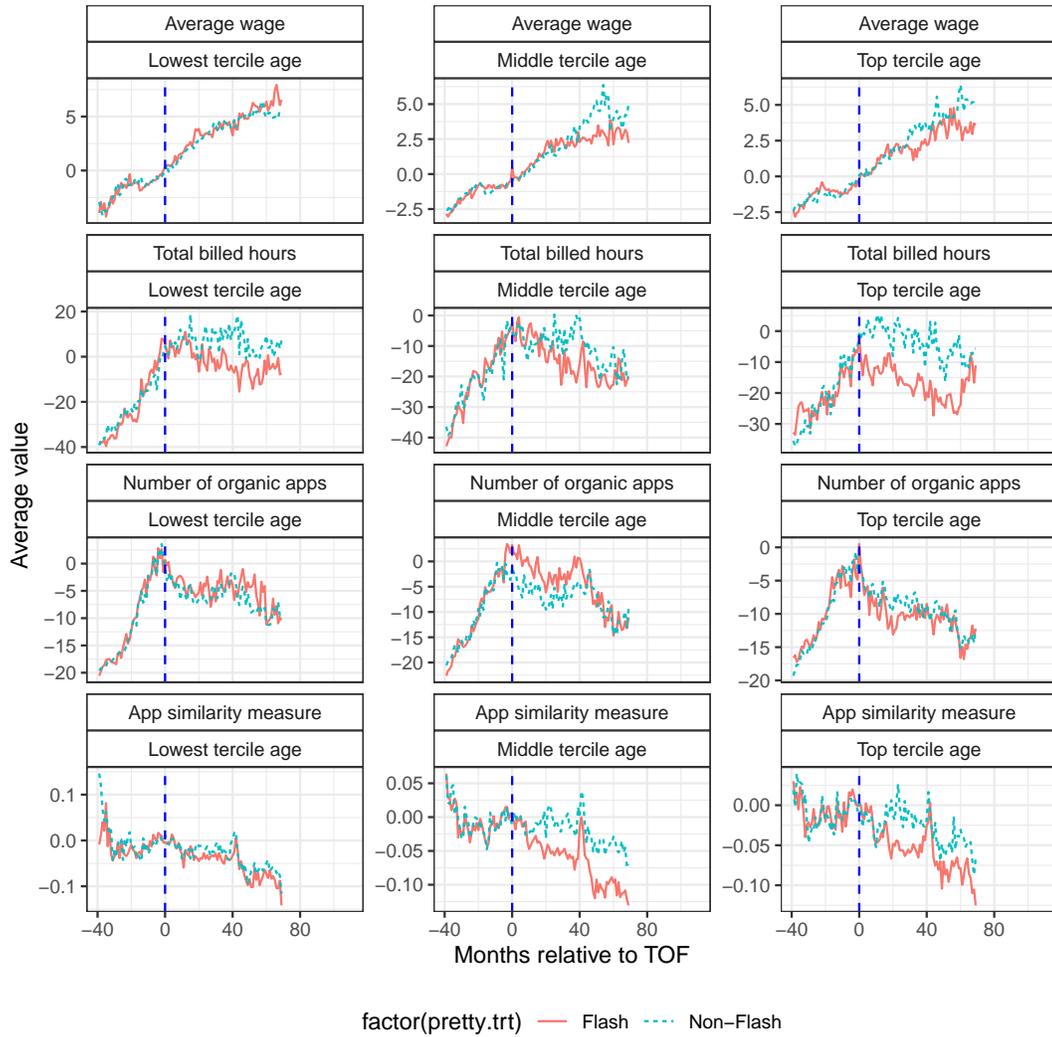
As Flash projects declined along a path towards zero demand, continuing to work on Flash projects may have come with a higher opportunity cost for younger workers than for older workers. Young workers have a longer career horizon, so may have experienced larger potential gains from climbing the learning curve in a new skill. On the other hand, given the skills based nature of the platform, developers may be considering a forward time-window that is short enough that developer age might not have a significant impact on workers’ human capital investment decisions.

We do not have access to direct measures of a worker’s age, but we can impute it from data provided by workers on their final year of schooling. The average worker in the sample is about 14.4 years past their final year of schooling.

We can examine if our main individual outcomes differ by age cohort. We split the sample of Flash developers into terciles according to their final year of schooling. Figure 9 illustrates how labor outcomes by cohort compared to those in the same cohort in the matched sample. In each panel, the orange (solid) line is for Flash developers and the blue (dashed) line is the matched developer group. The first row indicates that developers in the top two age cohorts experienced a reduction in wages, but there is no visible reduction in the cohort with the most recent final schooling year. This is consistent with a larger loss of Flash human capital in the older cohorts. We can observe a reduction in hours across all cohorts, but the effects are largest in the cohort with oldest workers, as measured by when they finished school.

The figures for submitted numbers of applications appear similar for Flash developers and the comparison group, although they are slightly higher for workers in the middle tercile. There is no observable change in the types of applications submitted by younger workers, who may not have accumulated much Flash human capital by TOF and may not have yet chosen to “focus” on Flash technologies. Workers in the older two groups made more significant adjustments in the types of applications they submitted, beginning at TOF.

Figure 9: Flash market outcomes by years since school



*Notes:* This figure shows how workers and workers' hours responded after TOF where workers are separated by the number of years they have been out of school. The top panel shows total hours worked per period. The middle panel shows the number of workers actively using the skill. The bottom panel shows the number of hours per active group.

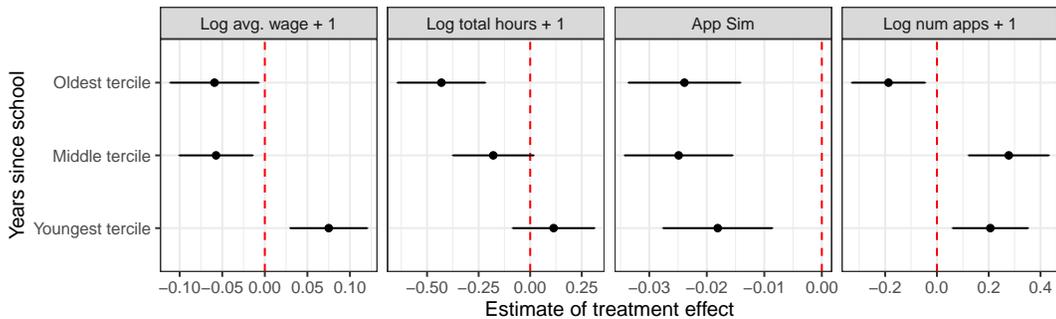
These illustrations are consistent with a story in which younger workers, who had little Flash human capital, abandoned Flash quickly enough that wages did not change in the short run for younger or older workers. As demand for Flash declined further, especially after Flash lost Android support in 2012, middle and older cohort workers who had more Flash human capital also had to move away from Flash, and move towards other skills.

We can also report the post-TOF aggregate effects between each age group and their matched developer group by estimating a specification of the following form, interacted the worker’s age cohort with the post and treatment indicator:

$$y_{it} = \beta_{AC(t)} \text{AgeCohort}_i \times (\text{POST}_t \times \text{TRT}_i) + \gamma_i + \delta_t + \epsilon_{it}. \quad (3)$$

Figure 10 reports  $\beta_{AC}$  for age cohorts, for each outcome. We can see that the oldest group of workers experienced large declines in wages and hours-worked. In contrast, if anything, younger workers saw an increase in wages and hours-worked. However, they also had to send more applications, though all workers changed their skill focus, as measured by application similarity.

Figure 10: Treatment effect by years since leaving school

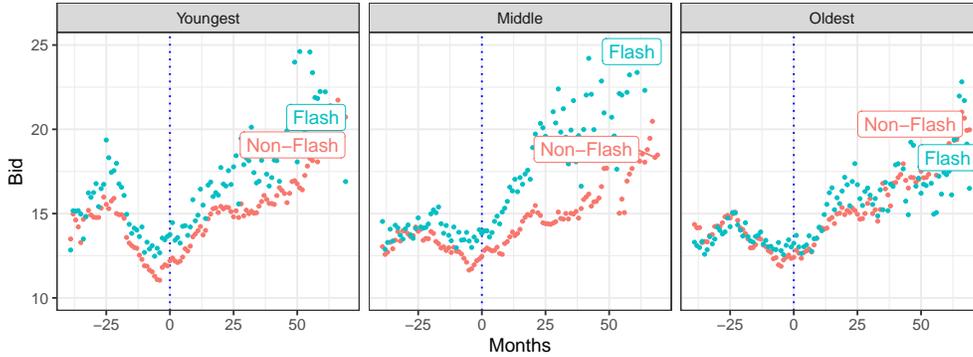


*Notes:* This figure illustrates differences in treatment effects for developers from different cohorts, measured by when they had their final year of schooling.

## 6.2 Younger workers exhibit differences in project bidding

In the model, workers either choose to exit the dying skill or stay, whereas in reality, workers have some ability to straddle both markets. Flash workers do

Figure 11: Project bid activity by age group



*Notes:* This figure illustrates bidding behavior for new projects by different developer age cohorts.

apply to both Flash and non-Flash jobs throughout the course of the panel. We can use this feature to assess transition strategies. Flash developers with longer career horizons might require a relative premium to continue working with Flash, whereas older workers with a shorter career horizon have far less of an incentive to do so.

Figure 11 illustrates project bid behavior for workers in the different age cohorts. It shows mean bids submitted for both Flash and non-Flash projects by Flash developers in each period. If workers switch to new skills that can make their human capital more valuable in the future, they should be willing to work on these projects at a discount.

The facet first from the left, for younger workers, suggests that bids submitted by younger workers follow such a pattern. They require higher pay to work on Flash projects, which did not have a future, than they did for working on projects using other technical skills. We observe a similar bifurcation for workers in the middle tercile age cohort, and the separation between these bid categories is larger, which is consistent with workers in this cohort having accumulated more Flash human capital than younger workers.

In contrast, for older workers, any human capital obtained by working on new skills may be less valuable, so a bifurcation in bids is less visible. If workers are not as concerned about the future value of their skills, there is no reason for them to forego working on Flash projects at a higher wage.<sup>19</sup>

<sup>19</sup>It is also possible that differences in bids for Flash projects and other projects reflect

### 6.3 Alternative skills in the portfolio and adjustment

We can also look at workers who were on different points along the investment frontier. In Figure 12, workers' skill portfolios are measured in this application using data they self-report. Workers' skill portfolios are made visible to buyers in the market. There is no indication in the portfolio data of the amount of skill that workers have with each of these technologies. We also do not know when workers acquired these skills. However, most workers on this platform tend to enter their skills when they first join the platform and leave them unchanged thereafter. To test how worker skills impact outcomes, within the treated group, we use the following specification.

$$y_{it} = \beta (\text{SKILL}_i \times \text{POST}_t) + \gamma_i + \delta_t + \epsilon_{it}$$

This estimates a simplified (binary) version of how being located at different points along the skill investment frontier impacted developer outcomes post-TOF. Each point in Figure 12 corresponds to an estimate ( $\beta$ ) on the interaction effect between POST and SKILL. We compare three specific points along this frontier.

- Developers for whom Adobe skills comprised more than 50% of their skill portfolio
- Developers who were familiar with HTML5, viewed as an increasingly popular alternative to Flash.
- Developers who were also familiar with technical programming languages, specifically C++ or Java

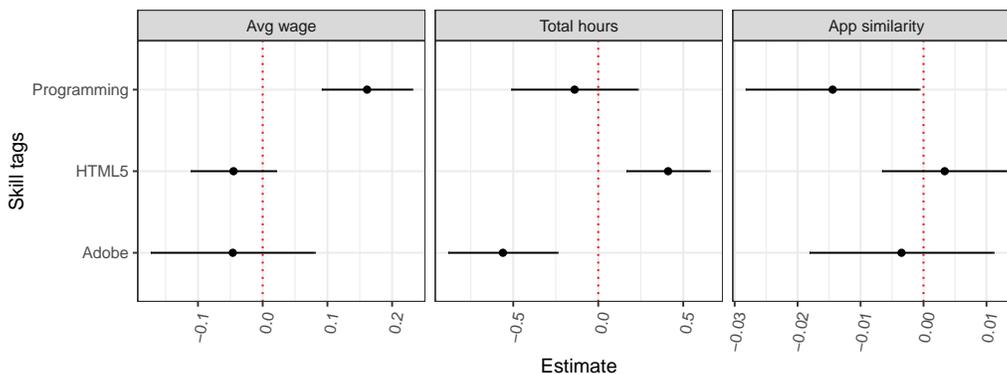
In Figure 12, we see that having greater specialization in the Adobe family of technologies (e.g. Adobe Dreamweaver or Adobe Illustrator) makes workers more vulnerable to Flash decline: for these workers, there was no change in wage, but a significant decline in hours. In contrast, Flash developers who were familiar with other programming technologies earned higher hourly wages than those who were not post-TOF, which may have been the case if it was relatively easy for them to transition to other high paying skills. Flash

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tastes for working with one technology or another. Developers are known to have strong preferences for the tools with which they work. However, the timing and pattern of bidding across age groups suggests that workers are considering the future value of skills in their bidding choices.

developers who were familiar with HTML5 experienced an increase in hours rather than a reduction, which would have been consistent with a rising incidence of Flash-HTML5 conversion projects or rising demand for HTML5 more generally.

Figure 12: Differences in outcomes by workers’ skills



*Notes:* This figure illustrates differences in outcomes for Flash developers with different skill endowments.

## 7 Conclusion

Our main empirical finding is that despite a large reduction in demand for Flash skills, wages changed very little, due in part to how rapidly workers adapted to this change. The supply of Flash workers proved to be remarkably elastic with no discernible evidence of a decline in wages, in part because of rapid adjustment by the supply side of the market. The adjustment was rapid because workers were forward-looking about human capital choices.

In terms of generalizability, our results are derived from a particular context where technological shocks are commonplace, the pace of technological change is quick, and there are relatively few frictions associated with moving to new technologies or employers. Furthermore, there are many “nearby” skills that affected workers can switch to. Other skills might offer fewer adjustment options to affected workers, though our results do suggest what features seem to help adjustment—namely a relatively easy way to gain on-the-job training. The relatively low stakes of hiring decisions and the short-duration of the relationships on the platform we study might be important

factors for helping workers adjust. That being said, it is disconcerting to note that even years after the decline of Flash, the most Flash-focused workers seem to have lower hours-worked and higher application intensity. The cause is unlikely to be a change in preferences.

Our results are consistent with the labor market not being a significant impediment to technology adoption: the “old” skill did not become relatively cheaper, and the price of “new” (at least to Flash workers) skills would, if anything, fall, as supply increased and/or workers were willing to work at a discount to increase their human capital. If workers quickly move to where the demand will be, the notion of a general skills mismatch seems unlikely (Marinescu and Rathelot, 2018).

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## A Surveys of Flash workers

To gain additional insight into the adjustment process, we surveyed a sample of Flash workers who had been active on the platform at the time of TOF. Surveyed workers perceived Flash’s dim future contemporaneously, and felt that they needed to switch to other skills. Respondents reported that their primary adjustment strategy was to learn new skills, and they did so by taking on projects in skills they wished to learn. This “earn while you learn” strategy (Tambe et al., 2020) was the most important method and was regarded as substantially more important than more traditional approaches, such as reading books and taking classes. Our results support the view that learning-by-doing is particularly important for new technologies (Bessen, 2003, 2016).

Surveyed workers reported a willingness to lower rates to obtain work in new skills—a margin of adjustment reported in other contexts but which might be particularly important in IT. In the IT sector, there is typically no additional physical capital required to acquire some skill, remote work/offshoring is comparatively easy and change is too fast for formal education to play much of a role (Barley and Kunda, 2011; O’Mahony and Bechky, 2006; Ang et al., 2002; Mithas and Krishnan, 2008). This feature of IT—rapid technological change that makes skills obsolete quickly—has recently been highlighted by Deming and Noray (2018).

Given the potential size of the Flash human capital investment, it is not surprising that many developers focusing on Flash described themselves as “Flash developers” specifically and expressed anger about the decline of Flash in our survey.<sup>20</sup>

In our survey of Flash workers, many respondents mentioned Apple’s role in Flash’s demise without being prompted:

“since Steve Jobs’ infamous speech about Flash, there has been a decline in the use of Flash across the web”; “people are more interested in other languages [sic] due to the reason that Flash is not supported by iphones and Ipads etc.”; “Steve Jobs not letting Flash platform on Apple devices is the primary reason [for the

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<sup>20</sup>One respondent wrote: “steve jobs wrote a nasty little hit piece before he died and that really was a turning point. before that me and my partner were working for big clients, making good money, even working with Adobe itself. hahaha he ruined everything. thanks for nothing steve!”

decline].”; “steve jobs wrote a nasty little hit piece before he died and that really was a turning point.”

## **A.1 Survey responses**

We surveyed Flash workers who were active on the platform prior to TOF. Survey questions were based on responses from two prior rounds of pilot surveys, which elicited free-text responses on the nature of Flash development, technical skill obsolescence, and the impact that changes in the Flash market had on them. Survey respondents were paid \$10 to complete the survey. The data were collected from respondents in late June and July of 2017. Of those who were invited to take the survey, 43% participated, giving us a total survey sample size of 186.

## **A.2 Exiting or staying?**

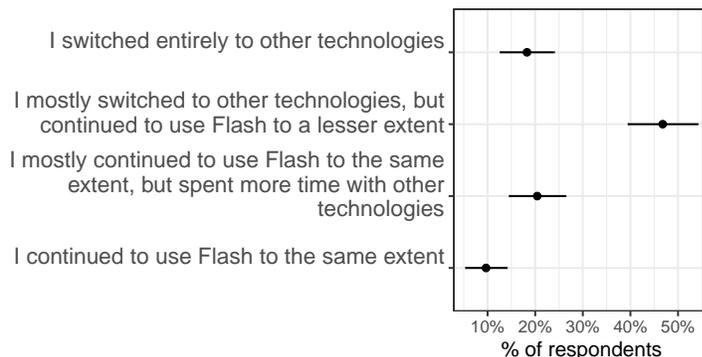
We asked respondents how perceived changes in the market for Flash skills affected their use of Flash. We wanted to know if the experiences of the surveyed workers matched our empirical results showing large declines in active Flash workers. The question we asked was: “If you noticed changes [in the labor market for Flash], how, if at all, did this impact your use of Flash for development?” We restricted possible answers to: 1) continued to use Flash to the same extent, 2) mostly continued to use Flash but switched over to some other technologies, 3) mostly switched but continued to use some Flash, or 4) switched entirely to other technologies.

The percentage of respondents choosing each possible answer is plotted in Figure 13. Of the respondents, about 65% reported switching to other technologies either completely or to a large extent. 90% reported at least some reduction in the extent to which they used Flash. Survey responses clearly support the notion of a decline in Flash on the supply side of the labor market, but it also is consistent with at least some workers being “stayers.”

## **A.3 Reported effects of the Flash decline on wages and hours**

A key finding in our empirical work was large declines in hours-worked in Flash but minimal changes in wages. We asked Flash workers how they perceived changes in the Flash market with respect to wages and project avail-

Figure 13: Responses to the question: “If you noticed changes [in the labor market for Flash], how, if at all, did this impact your use of Flash for development?”



Notes: Responses to question on skills used post-TOF.

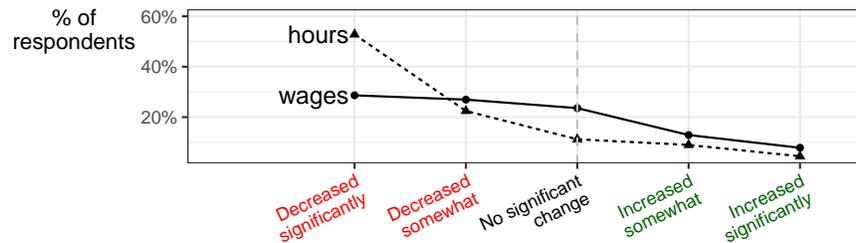
ability. We asked: “How have any changes in the market for Flash projects over the last several years impacted the overall wages you have earned using Flash?” and “How have any changes in the market for Flash projects over the last several years impacted the total number of hours you have spent on projects that use Flash?” Responses were limited to “Decreased significantly,” “Decreased somewhat,” “No significant change,” “Increased somewhat,” and “Increased significantly.” The percentages reporting each response are shown in Figure 14a, for both hours and wages.

The responses suggest there was a substantial decline in both wages and hours, but more workers report declines in hours than wages. About 50% of respondents experienced a significant decline in hours, but only about 30% of workers experienced a significant decline in wages. A smaller set of workers, about 10%, also reported experiencing a *rise* in hours and wages. That some workers report no decrease in their hours-worked is consistent with some number of incumbents sticking with Flash and our finding that hours-per-worker active in Flash actually rose post-TOF.

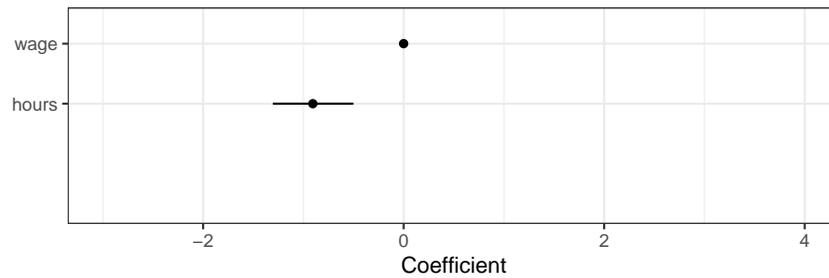
Given that our responses are ordered, we can also estimate an ordered logit. The outcome is the respondent’s characterization (“Decreased significantly”, “Decreased somewhat” etc.) and the independent variable is whether it was the “hours” question or the “wages” question. An advantage of also estimating an ordered logit is that we can be more confident that the difference in responses we see in the counts is likely not due to sampling variation.

Figure 14: Responses to the questions: “How have any changes in the market for Flash projects over the last several years impacted X” where X = “the overall wages you have earned using Flash?” and X = “the total number of hours you have spent on projects that use Flash?”

(a) Fraction of respondents choosing each characterization, by hours and wages



(b) Ordered logit model with cut-points and latent index effects



Notes: Top facet reports the percentage of respondents selecting the various possible responses. The bottom facet shows coefficients and cut-points for an ordered logit model.

The ordered logit coefficient on question type is shown in Figure 14b, along with the point estimates for the cut points between levels. Mechanically, the confidence interval on the coefficient for the omitted category is 0, as there is also uncertainty in the cut-point estimates (which we do not plot). The ordered logit coefficients provide clear evidence that the survey respondents perceived larger declines in hours than wages.

In their free text answers, respondents noted the drop in availability of Flash jobs, but some also pointed out that this was accompanied by a rise in offered wages. When asked to describe changes in the market for Adobe Flash projects between 2010 and 2017,<sup>21</sup> some selected responses were:

“Definitely a drop in available jobs/job postings. I have found the offer rate has gone up (maybe since the talent pool is smaller now).”

“The number of available jobs is far fewer in 2017 than in 2010. The types of Flash projects I get are more interesting and difficult than I used to, which may be in part because I have more experience, but may also be because the available jobs in Action-Script are highly specialist, as the more general usage of Flash has shifted to HTML5.”

“Since Steve Jobs’ infamous speech about Flash, there has been a decline in the use of Flash across the web. The number of jobs posted has declined, the types of projects were focused mainly on games & video players, interestingly, the budgets for Flash projects have risen due to the decline in the number of available Flash developer.”

Like this last respondent, others also cited the post by Steve Jobs as a triggering event in the decline of demand for Flash projects.<sup>22</sup>

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<sup>21</sup>We asked “Describe any changes you have noticed in the market for Adobe Flash projects between 2010 and 2017—either the numbers of jobs posted, the offer rate, or types of projects. If you began working with Adobe Flash after 2010, describe any changes you have seen in the market since you joined.”

<sup>22</sup>We asked “If you have noticed changes, what business, economic, or technological factors, do you feel, were the primary CAUSES of these changes in the market for Flash projects?”

“Steve Jobs not letting Flash platform on Apple devices is the primary reason. It was not big issue, but the way flash was portrayed [sic] as evil, people could not understand the whole scenario. Secondary is Android ditching Flash.”

“there was a campaign against flash for a long time and adobe really fumbled the ball, never defending it or improving it appropriately. steve jobs wrote a nasty little hit piece before he died and that really was a turning point. before that me and my partner were working for big clients, making good money, even working with Adobe itself. hahaha he ruined everything. thanks for nothing steve! (but it’s really adobes fault for failing to handle the situation at all).”

#### **A.4 Learning new skills or falling back on old skills?**

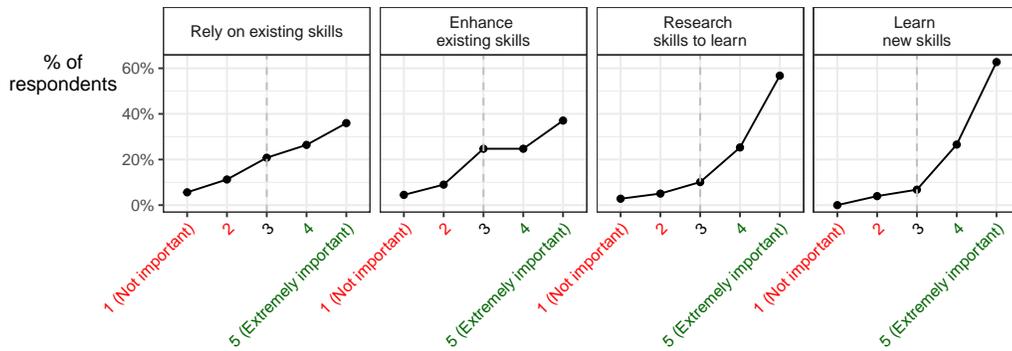
We wanted to understand whether workers were moving towards new skills or relying more on old skills that they had perhaps not been using when focused on Flash. We asked: “If you perceived a change in the market for Flash that compelled you to make adjustments, how important was each of the following adjustment strategies on a scale of 1 to 5?” We asked about four specific skill adjustment strategies—switching to existing skills, enhancing existing skills, researching new skills to learn, or learning new skills—on a Likert scale ranging from 1 (*not very important*) to 5 (*extremely important*).

Figure 15 reports the distribution of responses. All four strategies were relatively common in our sample of workers, but researching and switching to new skills was more common than falling back on existing skills. About 35% of respondents reported that they switched to existing skills in response to changes in the Flash market, whereas this number was over 60% for learning new skills.

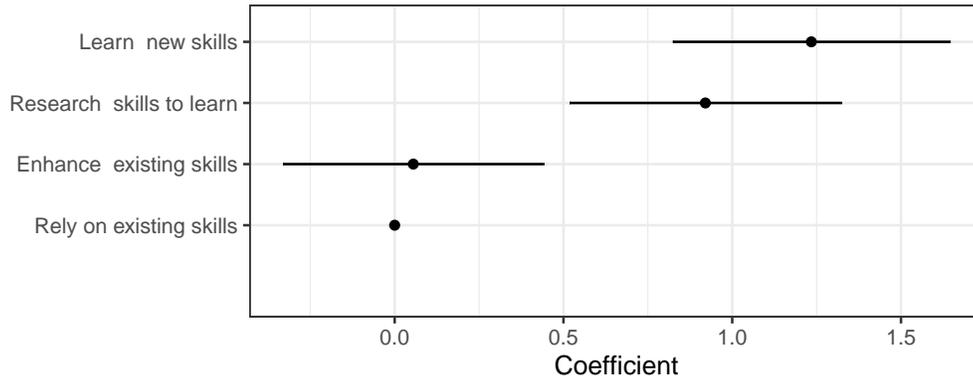
We can see the relatively greater importance of new skills in Figure 15a, where the ordered logit coefficient on the “Learn new skills” indicator is significantly higher than the two point estimates for the responses about relying on old skills.

Figure 15: Responses to question: “If you perceived a change in the market for Flash that compelled you to make adjustments, how important was each of the following adjustment strategies on a scale of 1 to 5?”

(a) Fraction of respondents choosing each possible response, by strategy



(b) Ordered logit model with cut-points and latent index effects



Notes: The top panel are the fractions of respondents choosing each category. The bottom panel are the point estimates and cut points for an ordered logit.

## A.5 Deciding which new skills to pursue

Given the large fraction of respondents reporting the need to learn new skills, we wanted to explore how they made the choice of which specific skills to pursue. We asked the question “On a scale of 1 to 5, how important are each of the following factors when deciding which technical skills to learn?” and then presented 7 possible factors: buzz/word-of-mouth, difficulty to learn, life span, maturity/stability, market wage, future demand and current demand.

Figure 16a plots the percentages choosing each rating for the 7 factors. Current and future demand are both ranked as being important by nearly every respondent, with the majority selecting “Extremely important.” Other factors, such as the wage, maturity and lifespan are all ranked as being important, but not as much as the two “demand” factors. Difficulty of learning the skill and buzz were only somewhat important. In short, respondents report being very forward-looking with respect to demand when selecting what skills to learn. This is also apparent in the ordered logit coefficients in Figure 16b, where the two demand-related coefficients—both current and future—stand out as particularly important.

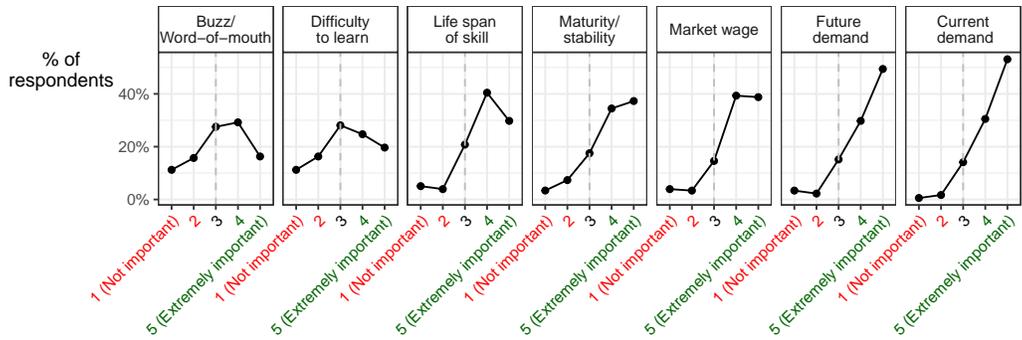
## A.6 Methods for learning new skills

After deciding which new skills to learn, workers have to choose how to learn those skills. Using the same 1-5 importance scale, we asked the question “When you switch to a new technology, how important are each of the following when learning the new skill?” about a number of possible methods. The possible sources were “Classroom,” “Friends,” “Online courses,” “Books,” “Unpaid projects,” “Online forums,” and “On-the-job.”

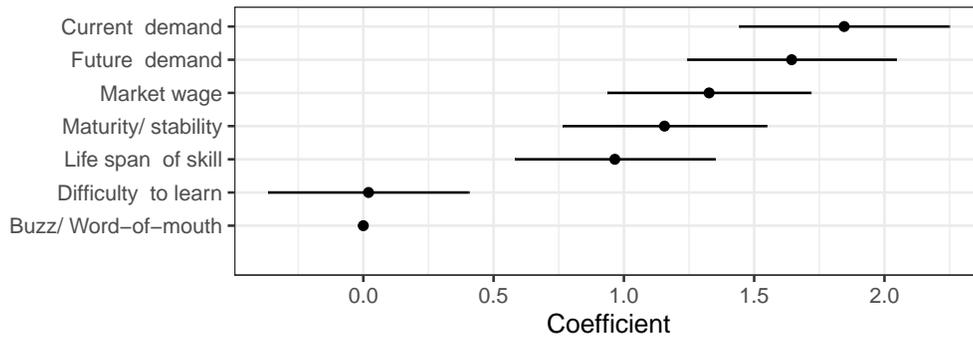
The distribution of respondents’ answers to this question is shown in Figure 17a. We can see that learning on-the-job and visiting online forums (e.g. websites such as Stack Overflow) were the two most common ways for respondents to learn new technologies. In Figure 17b, we can see that the ordered logit point estimates are both in the “Extremely important” region. The rest of the methods are of middling importance (near level 3) except for the classroom, which is ranked as much less important for learning new skills.

Figure 16: Responses to the question: “On a scale of 1 to 5, how important are each of the following factors when deciding which technical skills to learn?”

(a) Fraction of respondents choosing each possible response, by factor



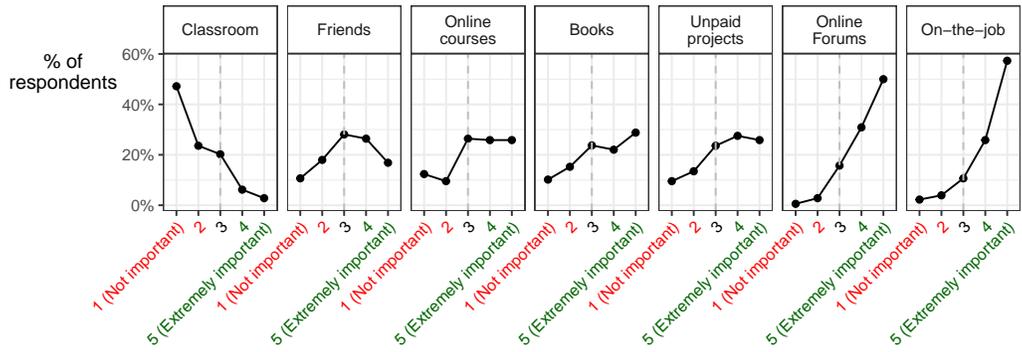
(b) Ordered logit model with cut-points and latent index effects



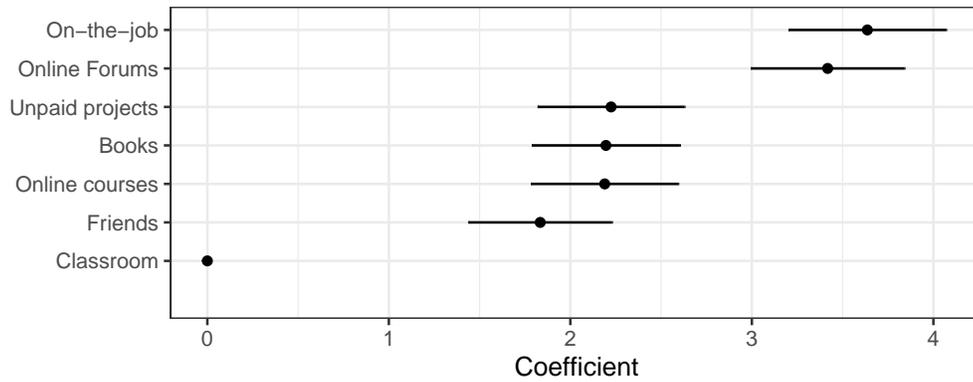
Notes: The top panel shows the fraction of respondents; the bottom panel the result of an ordered logit.

Figure 17: Responses to the question: “When you switch to a new technology, how important are each of the following when learning the new skill?”

(a) Fraction of respondents choosing each possible response, by method



(b) Ordered logit model with cut-points and latent index effects



*Notes:* This question asked what methods workers used to learn new skills. The top panel shows the distribution of responses. The bottom panel plots coefficients and cut-points for an ordered logit model.

## A.7 Bidding and learning on-the-job

Given that the most common way workers reported learning new skills was through on-the-job training, there is a chicken-and-egg problem—how do workers get work in a skill they do not yet possess?<sup>23</sup> One possibility is that workers take jobs while they are still relatively unskilled and/or offer a wage discount. We asked two questions to try to understand this approach: “When you work with new technical skills, how comfortable do you prefer to be—on a scale from 0 (never used it before) to 100 (fully proficient with the technology) – before starting to bid on projects that require that skill?” and “When you are beginning to work with new technical skills, how much of a discount, relative to the market wage, do you apply to your bid? Your answer should be on a scale of 0 (no discount, I bid at the FULL market wage) to 100 (I discount the whole price and do the project for FREE to sharpen my skills)?”

The distributions of the responses to these questions are shown in Figure 18 as histograms. On average, respondents noted that they only need to be about 66% comfortable with a new technology before beginning to work on projects requiring use of that technology. Moreover, the spread around this average is fairly wide, with a fair number of respondents saying that they only needed to be between 20%-60% comfortable with a skill to apply to projects requiring that skills.

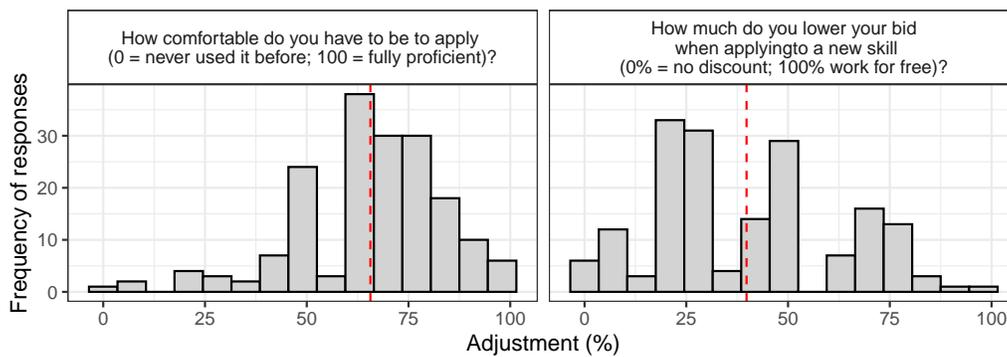
With respect to the wage, workers, on average, also noted that they lower their bids on projects for which they are using new skills. The mean value in the distribution of how much they lower their bid is about 40%. In other words, they bid at about 60% of the level at which they would normally bid when the skill is new. This reflects the lowered wage bid that we noted empirically for younger workers.

These responses are consistent with the notion that an exchange of wages for capital deepening affected workers’ choices as they switched to new projects. The discounts are large, implying that for new skills, the learning-by-doing component of the work is worth almost as much as the hourly wage itself, at least for these initial projects. If a large fraction of the work being done in any skill is done by workers with an eye towards the future, the notion of a future negative demand shock propagating back to the “present”—say by causing exit or deterring entry—is understandable.

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<sup>23</sup>The Theodore Roosevelt quote is apt here—“Whenever you are asked if you can do a job, tell ‘em, ‘Certainly I can!’ Then get busy and find out how to do it.”

Figure 18: Subjective measures of proficiency before bidding on work with a new skill and the amount of discount applied in bids



*Notes:* The left panel shows the distribution of responses to the question: “When you work with new technical skills, how comfortable do you prefer to be—on a scale from 0 (never used it before) to 100 fully proficient with the technology)—before starting to bid on projects that require that skill?” The right panel shows the distribution of responses to the question: “When you are beginning to work with new technical skills, how much of a discount, relative to the market wage, do you apply to your bid. Your answer should be on a scale of 0 (no discount, I bill at the FULL market wage) to 100 (I discount the whole price and do the project for FREE to sharpen my skills)?”

The free text responses also shed light on this learning-by-doing approach. For those workers who chose to switch to a new skills, we asked about project strategies.<sup>24</sup> A number of workers noted that when switching to a new technology, it was important to start with simpler projects, and build skill by working on projects.

“Switching to new technology implies that you cannot directly go to expert level projects. It requires starting with easy level and enhance your learning as you work more on live projects.”

“When working with a new technology, I start with simpler projects compared to what I would normally work in using a technology I have already been using for a long time. As I get more projects in with the new tech, I start applying for more complex jobs.”

To put this in terms of our model, the respondents are claiming that  $y < 1$  but that working in the technology can raise productivity. Finally, we asked workers about their bidding strategies when switching to new projects.<sup>25</sup> The responses to this question were supportive of the notion that workers tend to bid lower for projects where they are using new skills. In fact, a key theme of the responses to this question was the idea of being paid while learning.

“When switching to a new technology, I start with lower bids first, and then move on to high bids as I gain experience.”

“IF I was switching to say some javascript I would bid low to build up experience and a portfolio in that technology but still be paid something while learning. pretty good deal to get paid anything at all if you’re learning a bunch while you go.”

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<sup>24</sup>We asked “How, if it all, does switching to a new technology affect the types of projects you select?”

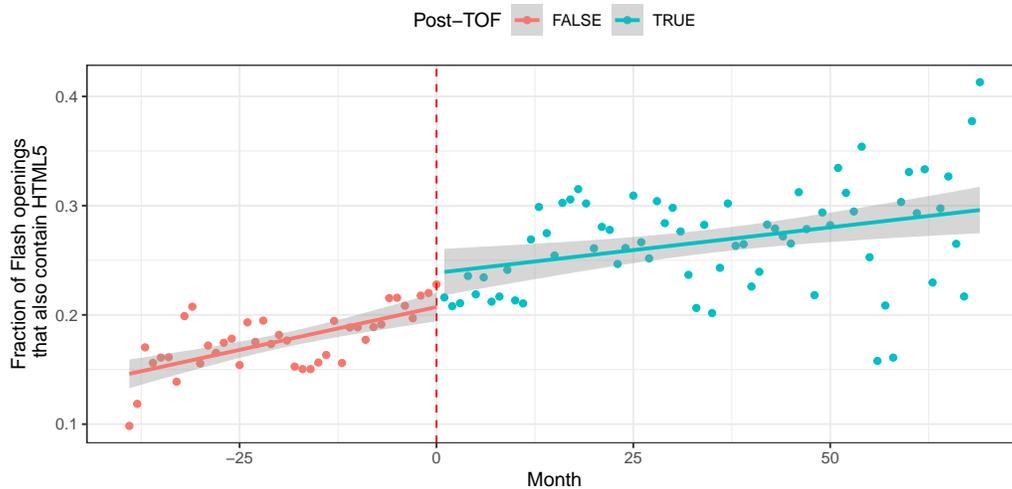
<sup>25</sup>We asked “How, if it all, does switching to a new technology affect the amount you bid on these projects?”

## B Robustness, sensitivity, and additional analyses

### B.1 Flash jobs requiring HTML5

Figure 19 shows the fraction of projects that contained both Flash and HTML5.

Figure 19: Fraction of Flash openings that also list HTML5



Notes: This figure plots the fraction of Flash openings over time that also list HTML 5.

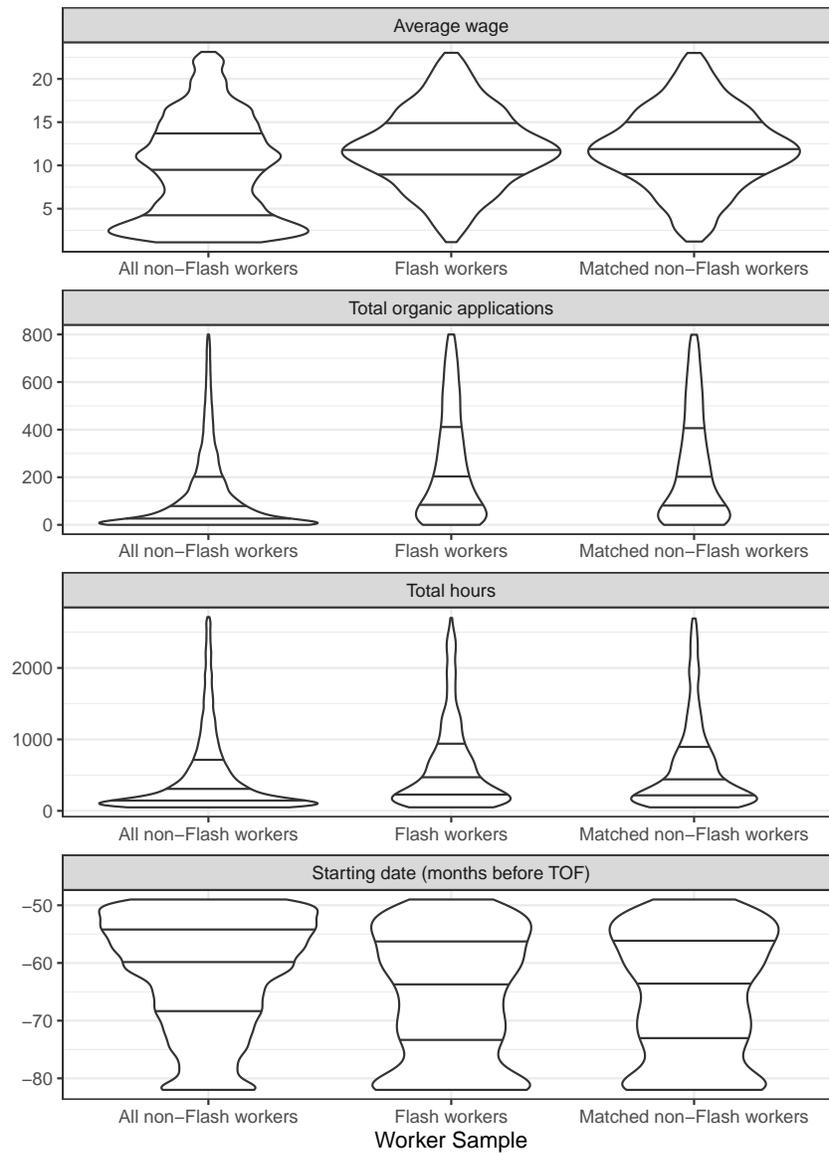
### B.2 Balance of matched sample

Figure 20 illustrates the distribution of worker attributes at TOF for the full population, the Flash worker sample, and their matches, which we use to construct the non-Flash group. We can see that the full population differs dramatically from the Flash sample, but that after matching, the distributions are quite similar.

### B.3 Panel definition and specification

In addition to choosing the independent variable, another alternative to this “long” panel form is to collapse everything into a pre/post period, creating a

Figure 20: Comparison of worker attribute distributions at TOF for the full platform population, the Flash sample, and the matched control group



*Notes:* This figure shows shows the distribution of worker attributes at TOF for the full sample, the Flash worker sample, and their matches.

short panel. With this structure, rather than have hours-worked per month as a dependent variable, the outcome is the total hours-worked before or after TOF. This structure has the benefit of making the panel more “balanced” for outcomes that are conditionally defined (e.g., the hourly wage, which we can only calculate for a given month if the worker works some number of hours). It also has the advantage of obviating [Bertrand et al. \(2004\)](#) problems. With this short panel approach, for outcomes that are counts (such as hours-worked), we divide the sum by the number of active periods, making effects comparable to the “long” panel estimates. In the short panel specification, we replace the period indicators with a POST indicator but maintain the worker-specific fixed effects. [Figure 21](#) plots all of the point estimates using the long and short panels, the two independent variable specifications, and different sample selection criteria. With the exception of the “any” outcomes (which get collapsed to nearly 100% in the short panel), all the point estimates are broadly similar.

## B.4 Extensive margin

[Figure 22](#) plots effects of TOF on whether a worker was active on the platform. We use two measures of activity: (1) whether they earned any money and (2) whether they sent any applications. All the point estimates are close to zero and are not conventionally significant. There is some evidence of a reduced probability of earning some amount of money, but also some evidence of them being more likely to send an application.

## B.5 Dynamic panel data model

We estimate the model

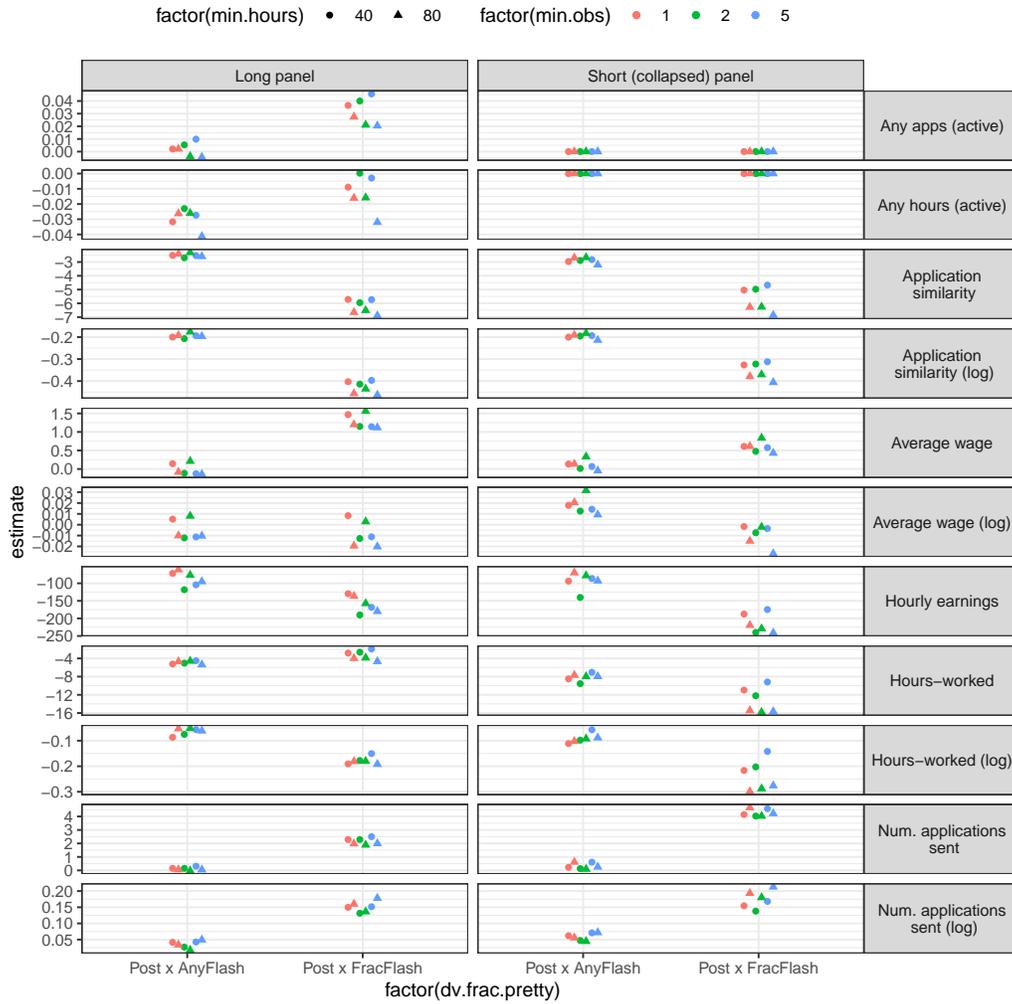
$$y_{it} = (\text{ANYFLASH}_i \times \text{POST}_t) \beta + \sum_{p=1}^k y_{i(t-p)} \lambda_p + \gamma_i + \delta_t + \epsilon_{it}. \quad (4)$$

We assume sequential exogeneity

$$\mathbf{E}[\epsilon_{it} | y_{it-1}, \dots, y_{i0}, \text{POST}_t, \dots, \text{POST}_0, \delta_t, \gamma_i] = 0. \quad (5)$$

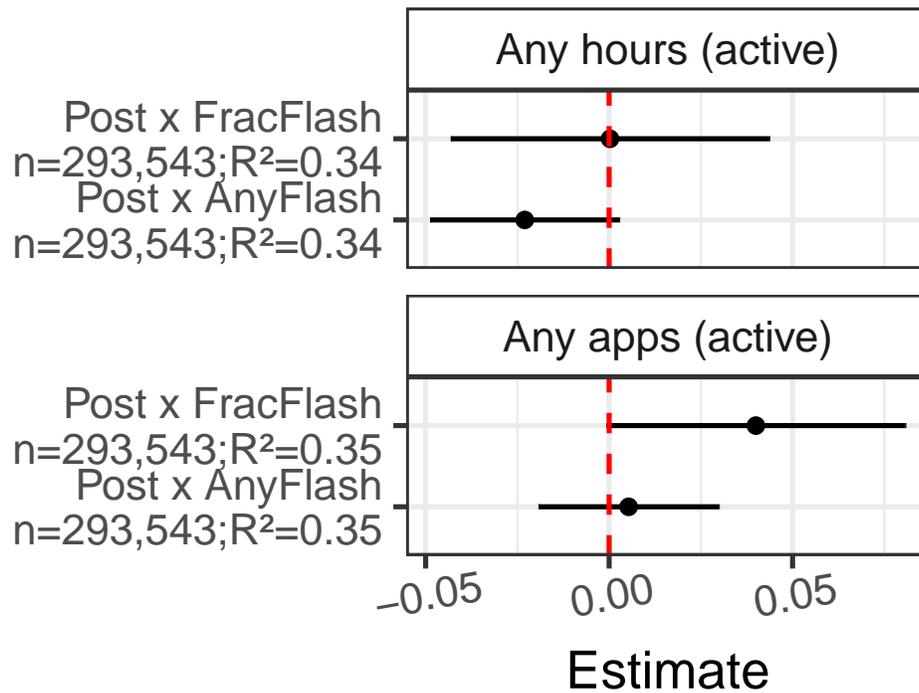
In [Figure 23](#), we report the long-run estimates of the TOF,  $\beta / (1 - \sum_k \lambda_p)$ . We use values of  $k$  from 1 to 4. We also report our baseline no lag version for comparison.

Figure 21: Point estimates for all models and specifications



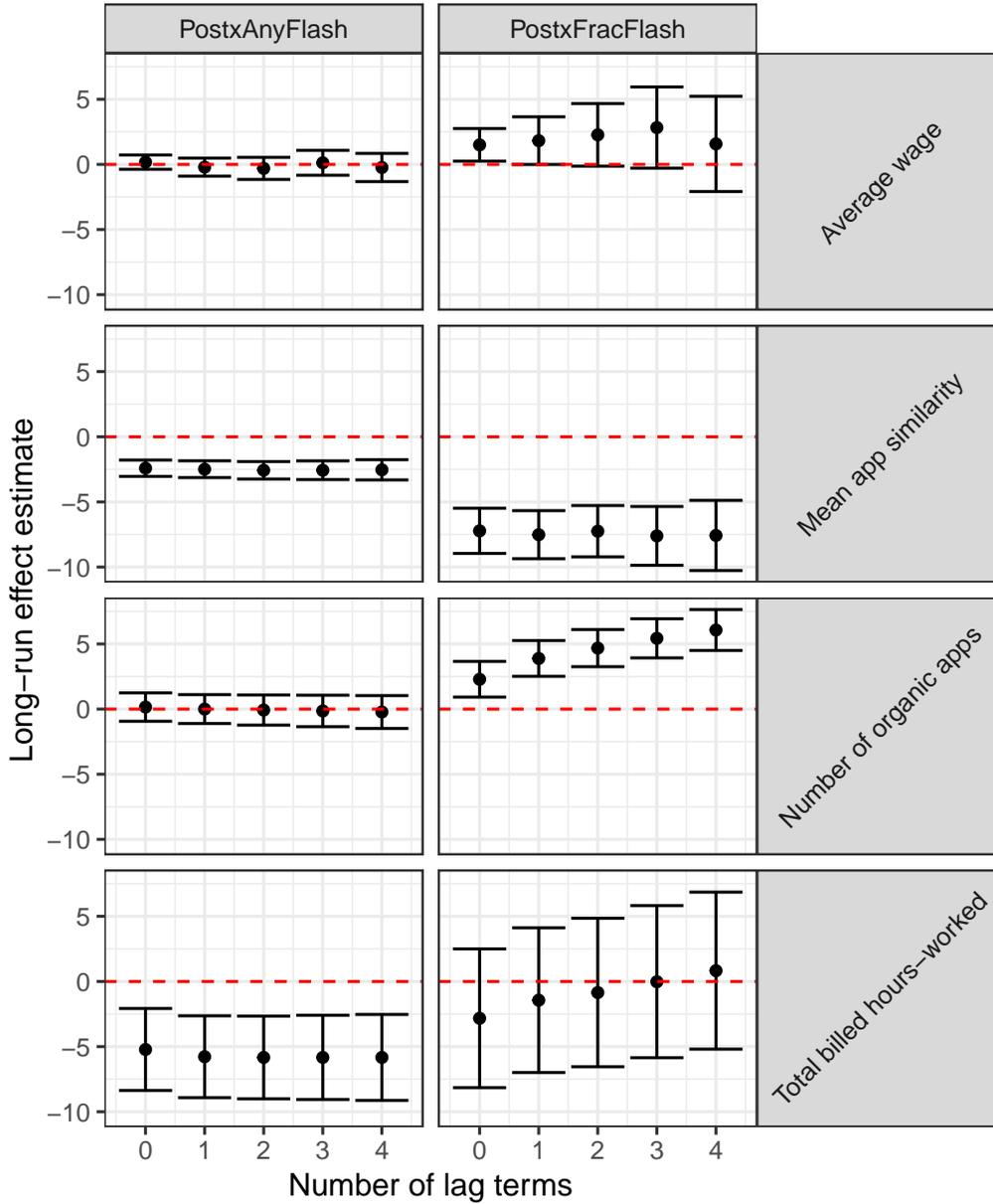
*Notes:* This figure plots all of the point estimates using the long and short panels, the two independent variable specifications, and different sample selection criteria. With the exception of the “any” outcomes (which get collapsed to nearly 100% in the short panel), all the point estimates are broadly similar.

Figure 22: Effects of TOF letter on Flash worker outcomes



*Notes:* This figure reports estimates of  $\beta$  from Equation 1. We estimate models in which there is a single treatment indicator, ANYFLASH and models where the independent variable is FRACFLASH, which is the fraction of pre-TOF hours-worked that were on projects requiring Flash. Sample sizes for each regression are reported under the point estimates. Differences in sample sizes reflect the fact that the panel is unbalanced.

Figure 23: Effects of Flash decline using lagged dependent variable models



Notes: Dynamic panel data estimates.